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An Integrated Approach to Chemical EOR Opportunity Valuation: Technical, Economic, and Risk Considerations for Project Development Scenarios and Final Decision

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by

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Dedication

To God and His glory.

To my family and friends for their encouragement and support.

To all who find this work useful.

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An Integrated Approach to Chemical EOR Opportunity Valuation: Technical, Economic, and Risk Considerations for Project Development Scenarios and Final Decision

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Surfactant-polymer (SP) and alkali-surfactant-polymer (ASP) flooding has gained little traction among different tertiary recovery strategies such as thermal and miscible gas flooding; however, many mature onshore reservoirs could be potential candidates. More than four decades of research has detailed technical challenges and successes through laboratory experimentation, chemical flood simulation, and some pilot projects, which have provided technical screening procedures to efficiently filter unfeasible projects. Therefore, technical understanding seems sufficient to advance projects through early development stages; however, a project value identification and realization process ultimately dictates project implementation in the oil and gas industry, with technical feasibility merely supporting overall valuation and project feasibility. A quick early screening methodology integrating important project valuation criteria can efficiently assess large numbers of projects. The relatively few studies detailing chemical flooding valuation from just an economic standpoint reflects the need for an integrated process-oriented framework for quick early screening valuation of chemical flooding opportunities.

This study develops an integrated process-oriented framework for early screening and valuation, with an overall objective to quickly filter unfeasible projects based on valuation criteria, rather than technical feasibility alone. A reservoir-to-market model was developed, integrating information from laboratory experiments (phase behavior, core flood), field analogues (well performance and layout), facilities, rigs, costs, scheduling, and economics. Recently published ASP flood data of the central Xing2 area in Daqing, China was used for model inputs. A reservoir-to-market benchmark model for a typical mature onshore field was successfully built and tested, and could value projects using standard economic metrics (net present value, internal rate of return, value investment ratio, unit technical cost, and payback period). Model simplification was achieved through global sensitivity analysis. Using a mean-reversion oil price model, the oil price accounted for 98% of the total sensitivity. . Model efficiency was achieved through discretization of input parameter uncertainties, which sped the screening process. Decision-making between model alternatives given information and different states of nature was performed through decision-tree techniques based on overall project valuation. Overall, this study was novel and provided benefit as a robust, integrated process-oriented framework for chemical EOR project screening, valuation, and decision-making.

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CHAPTER 1: INTRODUCTION

INTRODUCTION

Field development plans for many oil fields throughout the world still have water flooding as the final recovery technique applied prior to abandonment. As a result, many mature reservoirs under water flood have low economic production rates despite having as much as 50 – 75% of the original oil still in place. However, many enhanced oil recovery (EOR) techniques, otherwise known as tertiary recovery, have been very successful in recovering oil beyond what water flooding would recover, with the main types being: thermal, chemical, and miscible CO_2/gas flooding. Manrique et al. (2010) performed a comprehensive study of EOR projects that occurred in the US during the past 40 years, showing the total number of projects peaked in the mid-1980s at 500 before tapering off to around 150 in the mid-2000s (Figure 1). However, with the recent increase in oil price to over $100/STB, planned EOR projects are again increasing both in the US and worldwide (Manrique et al., 2010).

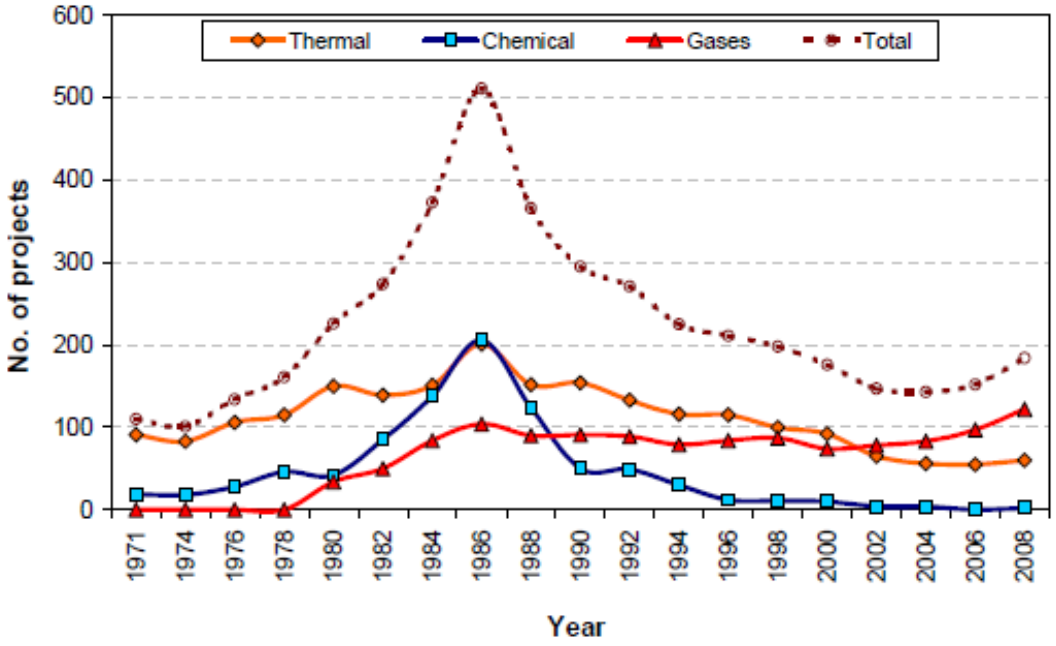

Figure 1: United States EOR projects from 1971 to 2008 (Manrique et al., 2010)

Surfactant-polymer (SP) and alkali-surfactant-polymer (ASP) flooding, generally known as chemical EOR, commonly uses one or more chemical agents, including: surfactant, co-surfactant, co-solvent, alkali, polymer, and/or electrolytes. Surfactant and co-surfactant reduce oil/water interfacial tension (IFT), resulting in the reduction of residual oil saturation, and therefore increasing the amount of mobile oil. Alkali can generate additional surfactant in situ and reduce surfactant adsorption (i.e. loss) on rock, while polymer improves mobility control and ultimately sweep/recovery efficiency. Chemical flooding that contains (but is not limited to) alkali, surfactant, and polymer is commonly referred to as ASP (i.e. alkali/surfactant/polymer) flooding. Recent advances in surfactant and polymer technology gives chemical EOR the potential to be applied to a wide range of different reservoir conditions and characteristics (Taber et al., 1997; Zhao et al., 2008). On the other hand, thermal EOR is generally limited to heavy oil plays, and

CO_2 flooding is limited by availability of a CO_2 source and miscibility pressure and temperature constraints.

Projects in the oil and gas industry are becoming increasingly capital-intensive and come with a number of technical challenges and risks; however, there is the opportunity to realize a great deal of value or reward if the project succeeds. Chemical EOR projects are no exception to a high-risk, high-reward project scenario, especially given the scarcity of field-scale, fully-commercial projects to serve as analogues. However, given the high demand for crude oil in today's market, abandoning fields after water flooding without screening or studying various EOR options may prevent full project value realization. A reservoir-to-market model can be an inexpensive approach to chemical EOR opportunity valuation, and ultimately determination of project feasibility and value realization. Therefore, this research aims to identify parameters that influence chemical EOR opportunity valuation, and demonstrate a general reservoir-to-market model that considers various inputs and analyses (production forecasts, scheduling, economics, facilities, etc.) that can ultimately serve as a basis for determining project feasibility.

PROBLEM STATEMENT / SCOPE OF RESEARCH

Chemical EOR has gained little traction among different tertiary recovery strategies; however, many mature onshore reservoirs could be potential candidates. More than four decades of research has detailed technical challenges and successes through laboratory experimentation, chemical flood simulation, and some pilot projects, which have provided technical screening procedures to efficiently filter unfeasible projects. Therefore, technical understanding seems sufficient to advance projects through early development stages; however, a project value identification and realization process

ultimately dictates project implementation in the oil and gas industry, with technical feasibility merely supporting overall valuation and project feasibility. Therefore, the main focus for early screening of chemical EOR projects should be on value identification; however, the literature does not contain an efficient, integrated process for chemical EOR projects.

Most major players in the oil and gas industry have adapted a stage-gate project management process (PMP) for opportunity realization (Walkup and Ligon, 2006). The aim of a PMP framework is to create greater value from projects while simultaneously protecting the interests of various stakeholders. The process details how value is created and delivered, beginning with value identification and ending with value realization; however, the process emphasizes the importance of creating value early in the project. Walkup and Ligon (2006) outline a five stage process, the first three stages are collectively called front-end loading and pertain to value creation, while the last two stages pertain to value realization where a project is executed and goes into operation.

Reservoir-to-market modeling is an integrated, inexpensive, and practical approach to assessing and ultimately creating value for a field-scale chemical EOR opportunity. The model integrates any technical understanding and/or data from laboratory and simulation study, facilities costs and constraints, rig/construction costs and schedules, production forecasts, and economic parameters among other things. However, in the early stages of a project when little data is known, a basic model can still be created to serve as a screening tool, and the model can be continually updated as more data is obtained in later stages of the project.

Any number of objective functions, whether cost functions or other production metrics, can be generated as output to compare among different modeling scenarios. For example Sanz and Miller (1994) discusses several different objective functions to

compare project scenarios, including the internal rate of return (IRR), net present value (NPV), profit to investment ratio (RPI), and payback period. In a reservoir-to-market model, numerical input parameters can be defined as distributions in order to describe parameter uncertainty ranges. Deterministic sensitivity of parameters can be modeled by selecting low (P90), mid (P50), or high (P10) values of various parameters; however, the model is capable of global sensitivity analysis using probabilistic / Monte Carlo simulation of input parameters followed by, for example, the Sobol method for analysis. Sensitivity analysis and other techniques like discretization can help simplify the model, and provide a setup to assess different development scenarios through decision tree analysis.

PetroVR software by Caesar Systems was chosen to create the reservoir-to-market models. PetroVR is commonly used in the oil and gas industry, and provides exploration and production (E&P) projects an integrated reservoir-to-market simulator of the entire business value chain. It is applicable for upstream development planning, providing decision-making support, integrated petroleum economics, and uncertainty analysis (for geology, engineering, and economics) (PetroVR User's Guide, 2000). PetroVR is capable of solving development problems by integrating many different aspects: reservoir volumetrics, drilling, reservoir development planning, facilities, project planning, economics, portfolio management, stochastic analysis, scenario analysis, and decision tree analysis. Although PetroVR provides a good software tool for assessing potential project value, a process methodology for populating and implementing the model is needed for efficient screening of chemical EOR opportunities.

MOTIVATION

The motivation for this work is to provide an integrated process for efficiently valuing and screening chemical EOR projects in the early development stages. A lot of research studies have detailed the technical aspects of chemical EOR, and a handful has discussed project valuation from an economic standpoint. There is a need though for a process-oriented framework that integrates all key project aspects (technical, economic, scheduling, equipment/facilities, etc.) for quick valuation and screening of chemical flooding opportunities early in the project development phase. It should essentially be designed to funnel a large number of projects through, filtering on only ones that show potential value.

Screening projects highlights the importance of a benchmark, which is a representative standard or reference to essentially serve as a starting point for building a reservoir-to-market model to value a project. The idea of a benchmark is to be general enough to adapt to a wide range of fields, but specific enough to have some degree of accuracy and make physical sense. For early project screening, the level of accuracy a benchmark offers is generally sufficient screen a project, and progress it to the next phase for more detailed study. One difficulty is the scarcity and/or absence of commercial-scale analogues to calibrate and provide inputs for the benchmarks. An additional motivation of this work is to develop a representative reservoir-to-market model benchmark for an onshore mature oilfield that could be adjusted to screen many other field of similar nature.

RESEARCH OBJECTIVES

The objectives of this research are the following:

1. Develop a process-oriented framework that integrates all key project aspects for quick valuation and screening of chemical flooding opportunities early in the project development phase.
2. Demonstrate the potential of a reservoir-to-market approach to determine chemical EOR opportunity valuation, and ultimately project feasibility.
3. Develop a reservoir-to-market model benchmark that can be adjusted and adapted to other potential chemical EOR opportunities of similar nature.
4. Identify parameters that influence the chemical EOR opportunity valuation, and techniques for model simplification and efficiency.

APPROACH AND METHODOLOGY

The main focus on this study is on early value identification and screening of chemical EOR opportunities, and the approach is to develop an integrated process-oriented framework based on all key valuation criteria, rather than technical feasibility alone. However, technical information is a crucial component of chemical EOR, and an extensive laboratory study was performed to establish a technical framework. Economics is another key component, and an extensive review of general project economics and principles was conducted. A third key component is an understanding of the project aspect, such as scheduling, facilities, risks, and uncertainties, and a review of general oilfield projects and specific chemical EOR case studies was conducted.

Once all key components of a chemical EOR project were identified, a reservoir-to-market model was developed, integrating information from laboratory experiments (phase behavior, core flood), field analogues (well performance and layout), facilities,

rigs, costs, scheduling, and economics. A reservoir-to-market benchmark model for a typical mature onshore field was successfully built and tested, and could value projects using standard economic metrics (net present value, internal rate of return, value investment ratio, unit technical cost, and payback period). Model simplification was achieved through global sensitivity analysis and discretization of input parameter uncertainties. Model efficiency was achieved through discretization, which sped the screening process. Decision-making between model alternatives given information and different states of nature was performed through decision-tree techniques based on overall project valuation. Overall, this study was novel and provided benefit as a robust, integrated process-oriented framework for early chemical EOR project screening, valuation, and decision-making.

SUMMARY OF CHAPTERS

This dissertation consists of eight chapters. Following the introductory chapter (Chapter 1), Chapter 2 provides a detailed summary on opportunity valuation and value creation/realization, and how it can be applied to a chemical EOR project through a reservoir-to-market modeling approach. Chapter 3 describes the technical aspects and theoretical/experimental basis for chemical EOR as a viable technology. This chapter also provides an experimental framework for the early stages of a chemical EOR project, with several recent examples of laboratory experimentation with challenging environments. Chapter 4 discusses the basic economic framework and workflow used for project valuation in reservoir-to-market analysis, as well as developing various objective function metrics for project screening. Chapter 5 describes the reservoir-to-market workflow for a chemical EOR project using a staged development strategy. This chapter also assesses various risk factors and uncertainty, and explores methods of de-risking and

assessment of project feasibility. Several surface and subsurface development concepts are provided, along with case studies to ultimately define a reservoir-to-market workflow benchmark for chemical EOR project screening. Chapter 6 details the reservoir-to-market modeling process, and generates an opportunity valuation assessment for a chemical EOR project benchmark. Chapter 7 details model simplification through sensitivity analysis and discretization, and performs a workflow for project screening through scenario/decision-tree analysis. Chapter 8 summarizes the results of the research, and provides recommendations for future research.

CHAPTER 2: OVERVIEW OF OPPORTUNITY VALUATION AND RESERVOIR-TO-MARKET APPROACH TO CHEMICAL EOR PROJECTS

INTRODUCTION

With projects in the oil and gas industry becoming increasingly capital-intensive, high-risk, and technically challenging, it is important to follow a systematic framework to valuing opportunities, and ultimately to be used for decision-making. Chemical EOR projects are no exception to high-risk and technical challenges given the limited number of historical commercial-scale projects; however, there is the opportunity to realize a great deal of value or reward if the project succeeds. Several studies focus on aspects of project management processes, opportunity valuation, and valuing of information, with the goal of more effectively identifying value early in a project's life, enabling informed decision-making, and ultimately realizing the greatest value during project execution and operation.

DEFINING OPPORTUNITY VALUATION

When implementing an opportunity realization process for a chemical EOR project, it is important to demarcate value identification and value realization phases of a project. Walkup and Ligon (2006) detail a stage-gate project management process (PMP) that is aimed to create greater value delivery from projects by segregating identification and realization aspects, while simultaneously protecting the interests of various stakeholders (Figure 2). Five different phases are contained in the process, with a decision gate separating each phase. Decision gates allow for a formal review of the value creation in a particular phase, and end with a decision by a decision review board to discard the project, redo the current and/or prior phase, or authorize a move into the next

phase. The first three stages of the process are collectively called front-end loading and pertain mostly to value identification, while the last two steps are where a project goes into execution and operation, and pertain mostly to value realization. Phase 1 is the Feasibility phase, which is the first phase of the front-end loading and overall project. During this phase, all the different technical and non-technical options are proposed and researched to determine if the project is indeed feasible. Feasibility can extend beyond a technical or economic definition, and often includes assessment of risk, alignment with corporate strategy, and engagement with stakeholders among other things. After considering many different possibilities, the decision review board decides whether the project is indeed feasible, and whether to proceed to Phase 2, which is the Selection phase, to narrow in on the best possible approach.

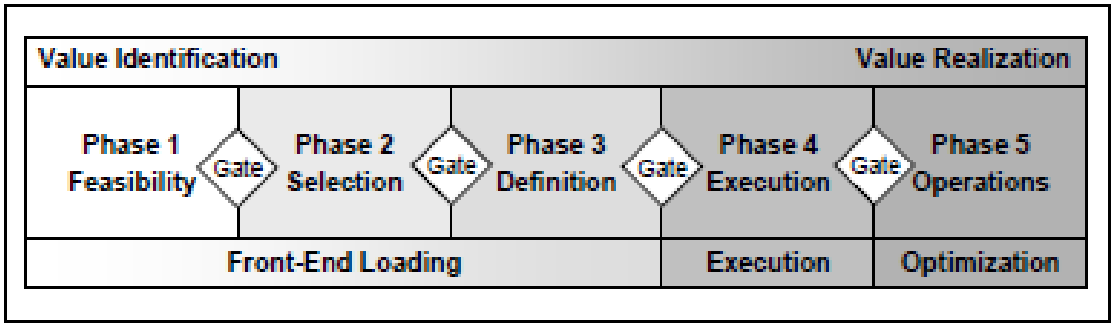

Figure 2: Five phases of project valuation, from value identification to realization (Walkup and Ligon, 2006).

The Selection phase essentially funnels all the development options into the best possible development plan for the project. Options are screened through concept evaluation using the best available information to specifically target shareholder value (Walkup and Ligon, 2006). From a value identification standpoint, the Selection phase is probably the most important of all the different phases given that rigorous and guided

concept evaluation is often performed during this phase; however, an exhaustive feasibility study performed during the Feasibility phase can certainly identify significant value early in the project as well. Ultimately though, the Selection phase is a very important step in value identification, as any significant future value creation will rely on how the selected project is executed and operated. Note also that the Selection phase must conclude with the selection of a specific plan and approval by the decision review board.

Phase III is the Definition phase, and its purpose is to describe, define, and fine-tune specific details of the selected development plan for movement to final investment decision (FID). FID occurs at the end of the Definition phase, which is also the end of the front-end-loading phase. Once FID has occurred, the process of procurement and construction for the project begins. In essence, FID can be viewed as a transition point between value identification and value realization (Walkup and Ligon, 2006).

Phases IV and V are the Execution and Operation phases, respectively, and are another point in the value chain where significant value can be either gained or lost depending on whether a project is executed and operated well or poorly. Walkup and Ligon (2006) discuss how the execution can involve hundreds of company staff and thousands of contractors, and that project management skills and experience are crucial in these phases for realizing the most amount of project value.

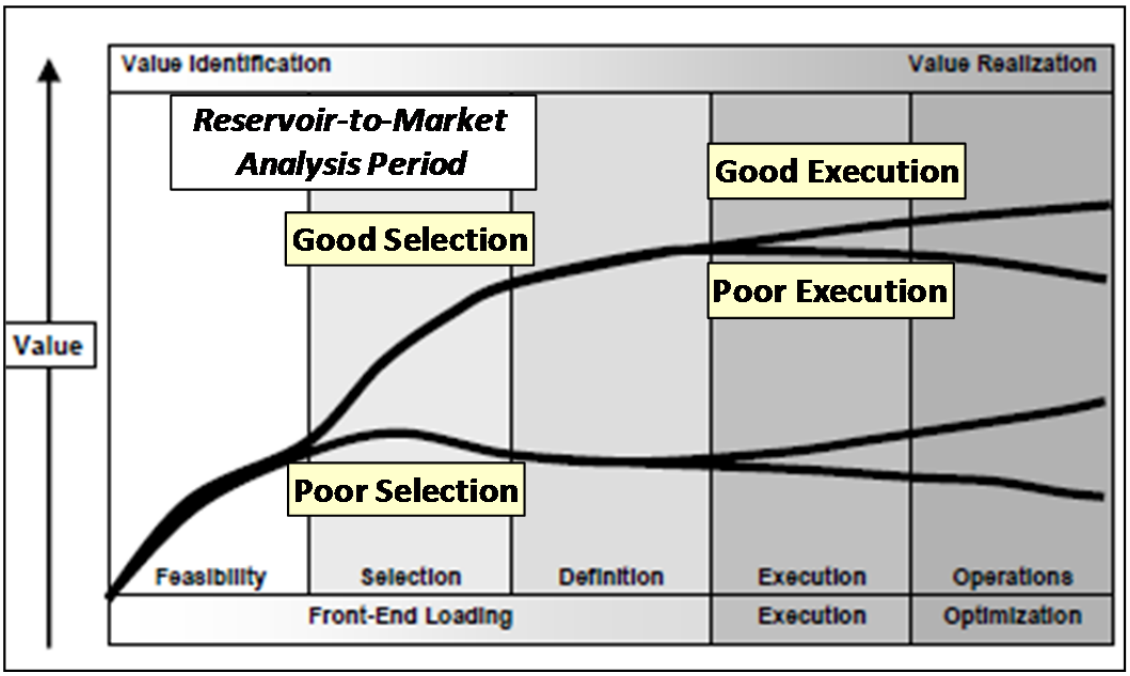

Figure 3: Four possible value-chain scenarios from value identification to realization (Walkup and Ligon, 2006).

Figure 3 shows a sketch of four different value-chain scenarios as they traverse the five different project phases (Walkup and Ligon, 2006). The sketch highlights the importance of value identification early in a project, where during the Selection phase there is a clear value demarcation between identifying a good project versus a mediocre one. In fact, mediocre versus good performance during the Execution and Operation phases can be less important to value realization than identifying a good project initially can be. Of course, the precursor to selecting a good project begins during the Feasibility phase, where all the different project options are explored and assessed for feasibility. The end of the Feasibility phase is then a crucial crossroad, and will ultimately determine if enough study has been done to determine if a project is capable of realizing sufficient value. In other words, this crossroad determines if a good or bad project has been

identified. Although carrying a project though its full lifecycle is the only way to conclude if it is good or bad (i.e. realizes low or high value), sufficient study during the Feasibility phase can help reduce the uncertainty to ensure that only good projects proceed to the Selection phase.

For chemical EOR projects specifically, because of the limited number of successful, commercial-scale projects, there is uncertainty in identifying and selecting a good project during the Selection phase. From a technical standpoint, chemical EOR literature contains a wealth of information ranging from laboratory experiments to simulation studies, and even to pilot projects. However, identifying good technical points for a project is only one part of the process, and ultimately quantifying an economic workflow for a project is what is needed to fully identify value. The literature though contains comparatively few detailed economic studies of chemical EOR projects. The next few sections will begin to outline a reservoir-to-market strategy for chemical EOR projects, with particular attention on integrating technical and economic aspects during the front-end-loading phases for value identification.

RESERVOIR-TO-MARKET APPROACH: IDENTIFYING VALUE FROM HYDROCARBON VOLUMES

A fundamental approach to oil and gas projects in general is to estimate the hydrocarbon volumes available, model and forecast how they can be recovered, and calculate the resultant market value. This volume-to-value approach or workflow aims at developing a streamlined, methodical basis for assessing an opportunity and making a final development/investment decision. The general steps consist of the following:

- Subsurface Characterization and Volumetrics
- Recovery Modeling

- Production Forecasting
- Costs and Scheduling
- Economic Valuation

Each step in the workflow can contain some degree of uncertainty with the parameters represented, and therefore parameters can be defined by a distribution rather than particular, discrete values. Uncertainty in chemical EOR projects, however, can differ from conventional oil and gas projects, which is important to realize. For example, although subsurface characterization and/or volumetrics can cause uncertainty for green field projects in primary production, chemical EOR projects frequently focus on mature fields where overall subsurface characterization can be better understood. However, other kinds of uncertainty are notable in chemical EOR projects, in particular: residual oil saturation reduction, mobility control, complicated chemical EOR recovery modeling and well performance, and chemical and facilities costs among others. The objective of a reservoir-to-market model is to capture a volume to value workflow and its uncertainty, and ultimately help optimize the value of an opportunity.

PETROVR

PetroVR software by Caesar Systems provides exploration and production (E&P) projects an integrated reservoir-to-market simulator of the entire business value chain. It is applicable for upstream development planning, providing decision-making support, integrated petroleum economics, and uncertainty analysis (for geology, engineering, and economics) (PetroVR User's Guide, 2000). PetroVR is capable of solving development problems by integrating many different aspects: reservoir volumetrics, drilling, reservoir development planning, facilities, project planning, economics, portfolio management, stochastic analysis, scenario analysis, and decision tree analysis. Oil and gas projects,

including chemical EOR, can have tremendous capital exposure before any hydrocarbons, and therefore revenue, is even produced. This exposure leads to greater risk, which emphasizes the importance of risk management. Therefore, significant value can be added through integration of reservoir-to-market parameters and considerations for project planning and forecasting, uncertainty consideration and stochastic analysis, and multiple development scenario and decision tree analysis (Fassihi et al, 1999). Figure 4 shows a generalized PetroVR workflow that inputs parameters (facilities specifications, reservoir characteristics, etc.) for given engineering scheduling and/or processes, which then runs various scenarios/decision trees of interest and/or Monte Carlo uncertainty analyses, and ultimately outputs economic metrics (i.e. objective functions) as which to assess project feasibility (PetroVR User's Guide, 2000).

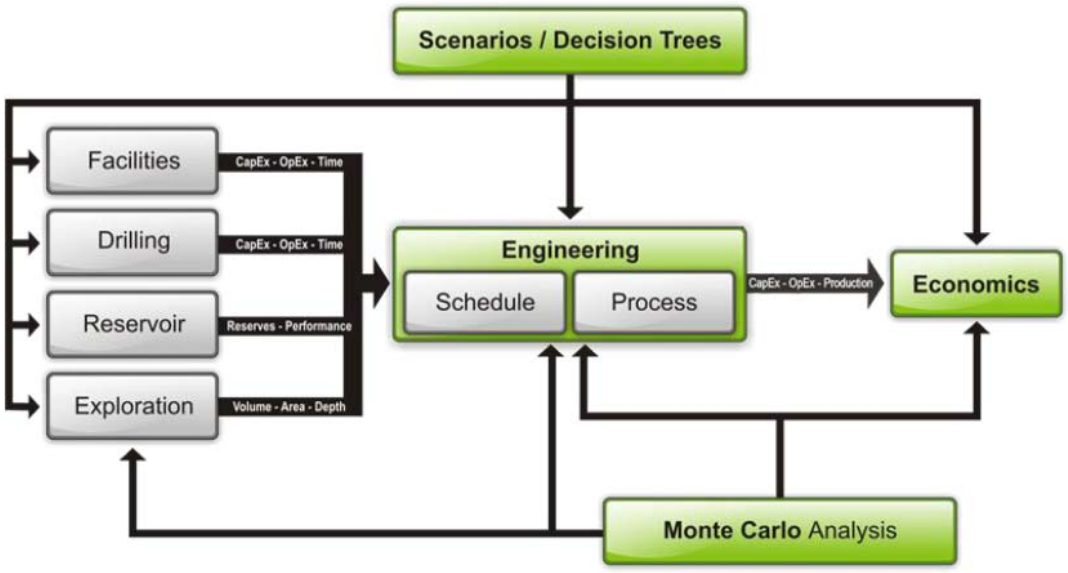

Figure 4: Generalized PetroVR workflow (PetroVR User's Guide, 2000)

The relevance of PetroVR for this work is that the software provides an easy, user-friendly platform to organize all the different project aspects such as reservoir properties and well performance; surface layout, rigs, and facilities; and costs and scheduling. Production forecasting is simulation is fairly straightforward, and occurs subject to various constraints with time, whether these constraints are well performance, facilities limitations, or drilling and construction time lag among others. Most economic metrics are pre-programmed into PetroVR, although some functions were coded in separately. Sensitivity analysis equations using the Sobol method were coded separately outside of PetroVR using Visual Basic script, and Monte Carlo output was post-processed without using PetroVR software.

Inputs and Analysis

A basic production stream model can be conceptualized as a hydrocarbon delivery system beginning with a source (reservoir) and ending with a receiver (export pipeline and/or refinery). Modeling the process of delivering reservoir volumes into market value requires defining a variety of different inputs, which can be generalized into the following categories: reservoir and wells; surface layout, rigs, and facilities; costs and schedules; and well performance. Most inputs depend on prior data from experimental, simulation, and/or actual field testing/production, as well as data from various vendors. Numerical input parameter can be described in terms of probability distributions, and PetroVR is programmed with eight standard distribution functions, including: cumulative, discrete, normal, log normal, truncated normal, truncated log normal, triangular, and uniform. For simplicity, the majority of parameters were described using a triangular distribution, with minimum, middle, and maximum numerical inputs describing the left boundary, top/peak, and right boundary of the distribution triangle,

respectively. Distributions allow for stochastic modeling / Monte Carlo simulation of an input deck.

Reservoir and Wells

A basic description of a reservoir is the volume in place, the recovery factor, and the fluids present. Chemical EOR projects generally consider oil reservoirs, and, although oil, water, and gas can all be modeled, oil is considered as the main fluid, with water and gas as subsidiary. In production modeling and forecasting, it is only necessary to describe the amount of oil that is available for recovery, and any associated gas or water that is produced with the oil. The most basic volumetric inputs to describe this include: oil in place, reservoir area, and recovery factor. Oil, water, and gas fluid properties are generally described in terms of gravities, formation volume factors, and gas-oil-ratio, with the option to include gas calorific value, and any associated components (sulfur, CO_2, etc.) with each fluid. For a more comprehensive model, it is possible to describe a volumetric input in more detail, and include: reservoir area, net pay, porosity, oil saturation, gas cap volume, and recovery factor. Sourcing and migration parameters can also be included (such as fetch area, source thickness, generation efficiency, migration efficiency, trap timing, and seal integrity), but for simplicity, this study focused on the basic volumetric parameters described previously (oil in place, reservoir area, and recovery factor).

Other than the volumes in place, basic production forecasting requires describing fluid/material inputs and outputs using injector and producer wells, respectively, as wells describe the movement of fluids from the reservoir to surface (or vice versa). Well performance is inputted as decline and injection curves, which are obtained from a chemical flood simulation study, analogue field data, or extrapolated from current field

data. The instantaneous rate/behavior of a well is a function of the decline curve, reserves, and the potential (initial rate) of each active producing well, and does not depend on historical drilling/abandonment. For a full-field production model, the question arises of whether all wells will be described uniquely or not. A unique scenario would be when decline/injection data is obtained from a full-field simulation or well history, where each well has its own unique data. Because the initial reserves of the wells are pre-defined, wells can remain isolated during the production simulation without communication. A non-unique scenario would be when injection/production data is obtained from a sector model simulation or total field production, and applied to each well or well-pattern in the full-field production model. In this case, describing well communication is usually important because actual well reserves are unknown. At a minimum, the number of wells is specified for a particular project phase (e.g. exploration, pilot, development); however, a well drainage area can be inputted. Defining a well drainage area can limit the possible number of wells in a particular area, and also limit the well reserves. Well reserves are generally a function of the reservoir reserves, drainage efficiency, well spacing, reservoir area, estimated ultimate recovery and recovery factor for the reservoir of interest.

Fluid communication between injectors and producers within the same reservoir can be modeled by a simple voidage replacement model. Voidage replacement is essentially an injection limit control, and it is based on net coverage of volumes, minus the efficiency of fluid placement in the right layer or spot. Voidage replacement deduction is distributed among all injectors. It is proportional to each well's performance, subject to the maximum facility injection capacity and injection water availability, and affected by formation volume factors for oil (B_o) and water (B_w). Initial cumulative fluid

production (oil, gas, water) and injection (water, gas) can be defined for mature reservoirs for the voidage replacement calculation.

Rigs, Surface Layout, and Facilities

Rigs are typically involved in a project development; however, chemical EOR projects of mature fields generally use existing wells. For mature fields, drilling rigs are less common, although workover rigs for replacing old tubing strings are usually used. Reservoir-to-market modeling should have the option for rigs, whether for drilling, completing, or well intervention, and therefore rigs should be briefly described. An individual rig is commonly associated with a single well for a certain period of time to complete a job. Cost inputs exist for rig mobilization/de-mobilization, and stand-by rate, whereas costs for rig activities (such as well drilling expense) are captured as input parameters for wells. Time inputs for rigs are inputted as rig availability (when a rig is mobilized) and seasonality (i.e. what periods of the year rig activity can occur), whereas time to complete a rig job (such as drilling time) is captured in the input parameters for wells.

The surface layout consists of all the physical surface components of a project from the well heads to the export pipelines. The well heads and well pads create the connection between the reservoir/wells of the subsurface, and the fluid injection/fluid processing systems on the surface. Injection wells are supported by a water injection system, which can receive fluid or chemicals from an external source or from a processing facility of produced fluids. Production wells are connected to fluid processing equipment (e.g. separators), which outputs saleable hydrocarbons to export pipelines, and non-saleable fluids to flair stacks, on-site disposal/injection, or transport for external disposal.

The purpose of surface facilities in a reservoir-to-market model is to receive, process, consume, and route fluids. They are defined by various constraints such as fluid capacity and flow rate, as well as capital and operating expenses. If facilities capacity is to be exceeded in a model at a particular point in time, wells production can be automatically constrained through choking, or wells can simply be shut-in automatically. Additional options can include automatic expansion of current facilities, or deferment of well drilling or activation to prevent additional fluid input.

For chemical EOR projects, surface facilities are more involved than for a simple water flood. Chemical injection systems supplying the injection wells will contain several feeds for chemical inputs (surfactant, polymer, etc.) as well as source water. Additional equipment such as mixers, pumps, and water treatment must be accounted for. Despite the complexities, chemical injection facilities can be simply defined by similar capacity and cost parameters (e.g. capital expense, fixed operating expense, and variable operating expense) as a simple water injection facility can. The unit cost (e.g. per barrel) of chemical injection fluid can be pre-calculated as a function of time by considering all the necessary chemical inputs from a chemical simulation study. Additionally, processing facilities of produced fluids can contain the necessary increase in capital or operating expense to account for additional treatment equipment for emulsion, polymer, etc.

Schedule and Cost

Scheduling is important in defining a timeline for how reservoir volumes will turn into market value, and scheduling is most simply characterized by a sequence of jobs. Jobs are defined as the main scheduled tasks performed under a given set of conditions. A job specifies a task (such as drilling a well), and the start condition (such as after rig mobilization). Jobs have participants involved, something that either performs the job (a

rig for instance in well drilling) or is the object (facility construction for instance). Often during development, a larger task, call it a macro-job, such as multi-well drilling, will consist of the same sub-job. For example, field development might involve a macro-job of drilling twelve 5-spot patterns, with the sub-job being the pads, wells, and surface facilities for a single 5-spot pattern. This also relates to an auto development option, which enables cloning of associated facilities that are directly receiving fluids from wells, and will be cloned when either the maximum connected wells is reached or when the well production potential has exceeded the facility capacity.

Chemical EOR projects have schedule and costs that differ from conventional water flooding. For example, these projects contain chemical costs (surfactant, polymer, and alkali), water treatment, injection facilities, and pilots to name a few. Scheduling is generally a phased scheduling, with the most extensive phasing occurring in the following order: laboratory testing, single-well pilot, multi-well single pattern pilot, multi-pattern pilot, commercial-scale.

Costs can be generalized into two different categories: capital expense (Capex) and operating expense (Opex), with Opex being further sub-categorized into fixed Opex and variable Opex. Capex is a fixed or sunk cost, expressed in money, while Opex is expressed as a rate, or money per time. However, to complicate things, Capex can be time dependent as well, and a particular job can contain both Capex and Opex. A drilling rig is an example of both time-dependent and fixed Capex, where fixed costs, such as mobilization/demobilization, and time dependent costs, such as daily rig rates, can be summed into one overall Capex value. It is important to note that all costs are associated with particular jobs, where costs are only being incurred when the job occurs. This modeling method has proven simple, effective, and allows for easy cost accountability.

Well Performance Inputs and Production Forecasting

For chemical EOR projects, accurately describing fluid injection and production relies heavily on simulation output from a chemical flood simulator or well history data from field injection/production. For example, the chemical flood simulator will have considered all chemical behavior obtained from microemulsion phase behavior and core flood data. The tabulated production output data from the simulator is the most accurate method, as simple analytical solutions such as decline curves would not accurately capture the chemical flood performance. Overall, a reservoir-to-market simulator aims to keep the production/injection well performance simple, with the more complicated reservoir and production modeling occurring in the chemical flood simulator.

Wells allow surface/subsurface transfer of fluid volumes, and defining the performance of these wells is important in a reservoir-to-market simulator. Well performance can be defined empirically by inputting fluid production versus time data obtained from simulation, analogues, or experience. Performance can also be defined analytically using various decline functions (exponential, hyperbolic, harmonic, etc.). The process of production forecasting occurs during the reservoir-to-market simulation, which is the time-dependent integration of the reservoir and well performance inputs, the surface facility constraints, and the project schedule. Although spreadsheet calculations can be used for production forecasting, commercial software such as PetroVR tends to be very robust, combining commercial and technical inputs, including uncertainty and risking inputs, and allowing easy design optimization.

Economics

Economic evaluation assesses the potential or expected value realization of an oil and gas project. Vaskas (1996) details an economic approach to optimizing surfactant flooding, and reports basic economic metrics to assess project feasibility. A basic

economic workflow models the various cash inflows (revenue, etc.) and outflows (expenses, taxes, etc.) over a project's life, and incremental or cumulative net cash flows (i.e. net income) can serve as metrics for the profitability or economic feasibility of a project. Because projects require a large capital investment, and often have a long time period before obtaining positive cash flows, it is important to calculate economic metrics during the front-end loading phases (e.g. using reservoir-to-market simulation techniques) to prove feasibility. There are several standard economic metrics, or objective functions, that give quantitative criteria to assess and/or screen projects. Sanz and Miller (1994) discuss commonly used metrics such as the internal rate of return (IRR), net present value (NPV), payback period, and profit to investment ratio (RPI), which is also the value to investment ratio (VIR). Each metric can serve a different purpose in assessing projects. NPV tends to be the best metric for assessing total expected returns from a project. IRR is essentially an effective rate of return expected from a project, and complements NPV in being the discount rate at which NPV equals zero. Payback period is a simple metric for determining the period of time required for returns to fully repay the original investment cost. Unit technical cost (UTC) is an additional metric to approximate the unit cost (e.g. $/STB) for oil production.

There are some relevant economics to chemical EOR projects in particular and potential hurdles that can trigger changes in chemical EOR projects. For a new (green field) development, development plans and economics for are often compared to a secondary recovery strategy where only waterflooding is used. UTC is a key metric, and of interest is the UTC of chemical EOR incremental recoverable oil volumes above what oil volumes a waterflood would recover. The UTC for chemical EOR is usually higher than waterflood, and, as long as the UTC is not much greater, the benefit of recovering additional oil may be advantageous. For re-development of a mature field (brown field),

chemical EOR post-waterflood can be characterized with economic metrics such as NPV, IRR, and payback period, where, if favorable relative to other primary or secondary recovery projects, it should be implemented. Cost and availability of chemicals can be a major hurdle for a chemical EOR project. Flooding design heavily depends on specific chemical quantities and quality consistency over a several year period. Any cost increases have to be incurred, and supply interruption in this may potentially have deleterious effects on the project's performance.

Stochastic Analysis, Monte Carlo Simulation

Stochastic analysis, which is frequently referred to as Monte Carlo analysis, is a method of calculating probabilistic outcomes given various input parameters each having a probability distribution. Input parameters can be defined using a variety of distribution functions, with the more standard ones including: cumulative, discrete, normal, log normal, truncated normal, truncated log normal, triangular, and uniform. A Monte Carlo analysis involves randomly selecting a particular input value from each distribution, and running a simulation (e.g. reservoir-to-market model) to arrive at particular output values. This process is generally run for many iterations to develop smooth probability distributions, or cumulative distribution functions, for output values. A Monte Carlo analysis has the advantage in capturing and representing the range of uncertainty in a project, compared to a possibly overly simplistic approach of selecting single, expected values as inputs to arrive at only one particular output value.

An important first step to Monte Carlo analysis is to establish an expected base case, where all parameters are defined by most probable (i.e. middle case), or expected values. Next a deterministic sensitivity analysis is run on both decision and stochastic parameters, usually by changing a single parameter and quantifying the change in output

value. This can help reduce the number of parameters used in Monte Carlo simulation if constrained by computation – a parameter having a large effect is kept for stochastic analysis, while a parameter with a small effect is removed from the simulation. As mentioned, parameters selected for stochastic analysis are generally, by nature, defined by a range of values, and a higher degree of uncertainty for a particular variable can be represented by a wider range about its mid-case value. A common example would be a cumulative distribution function, where the middle, or median, value is the expected value, or 50% probability value (i.e. P50), and the lower and upper bounds of the range are 90% (P90) and 10% (P10) probability values, respectively.

Scenario / Decision Tree Analysis

The purpose of decision tree analysis is to calculate an overall risk-weighted project value given results from several different development scenarios. A decision tree is also a useful tool to display decision variables (e.g. choices, risks, objectives, monetary gains, and investment analysis information). A decision tree layout contains a series of nodes and branches, with the branches being either intermediate branches, from one node to another, or end branches, from a node to an end result. Each end result represents a development scenario and has an associated value obtained from running a reservoir-to-market economic model. Nodes are commonly of two different types: decision nodes and chance nodes, each having two or more branches (Sanz and Miller, 1994). A decision node represents a point at which a decision is made (e.g. selecting either conventional or novel alkali), and has a value that is the highest of its branches, given that one would always make the decision of greatest value. Decision nodes are generally discrete, for example either a decision is taken or not, or one particular decision is taken (e.g. to develop one of several reservoir formations). A chance node represents a point where

more than one possible scenario can occur, with each branch feeding into the node having an associated probability and value. Branches from chance nodes are commonly expressed with discrete probability values, although chance nodes can be expressed as distributions. For example, a triangular distribution of net reservoir thickness, defined by a midpoint and low and high endpoint values, or a fault having a 50% chance to seal or not (leading to low or high production, respectively). The overall value of a chance node will be the sum of the probability weighted average of the associated branches. As with Monte Carlo analysis, an important first step to analyzing alternative development scenarios is to establish an expected base case at which to compare other possible scenarios.

For a chemical EOR project, scenario and decision tree analyses are an important part of the framework for selecting the concept. This stage is where several different concepts will be modeled and compared to determine which is most favorable with respect to economic metrics, risk, and other factors. For example, the concept of using alkali can be assessed by developing scenarios with and without alkali. Alkali can help reduce the surfactant concentration of a chemical formulation without compromising performance, but require the need for softened water. Less surfactant reduces costs, whereas softened water increases costs, and therefore the degree to which each affects overall project economics and which concept is most economically favorable is assessed in the decision-tree analysis.

UNCERTAINTY AND RISK

Uncertainty is the fact that something is not known and is usually characterized by a range of possible values or outcomes. It can be identified deterministically as discrete values, or probabilistically as a continuous distribution or probability density

function. As an initial starting point, uncertainty ranges can be defined by using fundamental principles/physics/mechanics, historical or analogue data (objective), and/or expertise (subjective). Acquiring additional data can help reduce the uncertainty, which narrows a distribution range or eliminates possible discrete values, but uncertainty will generally always exist in some form. Risk, on the other hand, is the probability of a future event that may have a positive or negative consequence. Negative risks can be actively managed, mitigated, reduced, or eliminated, although some risks (e.g. natural disasters or force majeure events) cannot be managed. Positive risks present an opportunity, and exposure can be maximized. Overall, it is possible to quantify risk to some degree through analyzing uncertainty.

When identifying the uncertainty of various input parameters, there are advantages and disadvantages in using deterministic versus probabilistic methods. Deterministic data is simplistic and easy to understand and communicate, but may be underrepresented and difficult to assign a probability of occurrence for each value. Probabilistic data is a nearly all-inclusive data range, can include a lot of sample data, and easily defines frequency of occurrence; however, it is difficult to communicate, augment data to a pre-defined distribution, and capture full uncertainty ranges in large simulation models.

Uncertainty analysis can be a rigorous, systematic process to identify and define the ranges and/or distributions of all input data. The first step is usually to identify all the parameters that could influence project development, and identify their possible ranges and/or distributions. For probabilistic values, generating probability density functions for the parameters is required. An optional, but useful second step would be to categorize and/or classify input parameters according to the degree (say low, medium, or high) to which they can influence more general outcomes (say well performance, facilities

constraints, etc.). Categorizing is often useful in understanding individual parameters, and categories can sometimes provide a simpler understanding of how the overall project value is influenced.

SUMMARY

This chapter provided an overview of the opportunity valuation and realization framework and process for oil and gas developments. A staged development approach using front-end engineering for value identification can significantly improve value realization during project execution and operation. A reservoir-to-market is a volume-to-value approach or workflow to screen projects and assist in the final investment decision, and includes the general steps of subsurface characterization and volumetrics, recovery modeling, production forecasting, costs and scheduling, and economic valuation. Each step of the workflow can contain uncertainty, which the reservoir-to-market model can be designed to handle.

CHAPTER 3: TECHNICAL ASPECTS AND RECENT ADVANCES OF CHEMICAL EOR

INTRODUCTION

Chemical EOR can be technically complex with many different elements of uncertainty, and it is important to identify the technical elements when building a reservoir-to-market model. A technical understanding can begin at the laboratory scale, where experimental work first considers molecular and fluid interactions based on the various chemical and phase interactions of different chemical formulations. These chemical formulations can be further analyzed through laboratory-scale chemical floods in core samples, which are meant to mimic field conditions. Chemical flood simulators can then be used to model laboratory-scale chemical floods, as well as upscale to pilot- or field-scale simulations. The importance of considering the entire laboratory-to-field scale process of experimental and/or simulation studies is to identify relevant input parameters and their uncertainty for a reservoir-to-market model. Additionally, field-scale simulations or well history data can ultimately serve as a production forecast input for a reservoir-to-market model as well.

CHEMICAL FORMULATIONS AND CHARACTERIZATION OF MICROEMULSION PROPERTIES OF OIL-WATER-SURFACTANT PHASE BEHAVIOR SYSTEMS

Chemical formulations designed for chemical EOR applications commonly contain one or more of the following chemicals: surfactants, co-surfactants, co-solvent, alkali, polymer, and electrolytes. Surfactants and co-surfactants generally receive the most attention because of their role in reducing oil/water interfacial tension (IFT). The subsequent sections discuss the roles of various chemicals in chemical formulation design.

CHEMICAL PROPERTIES AND ROLES

Surfactant

A chemical formulation can commonly contain one or more surfactants, co-solvent, alkali, polymer, and electrolytes, though surfactants generally receive the most attention for their role in reducing oil/water interfacial tension (IFT). Surfactants designed for chemical flooding commonly contain molecular functional groups that include a hydrophobe carbon-chain tail, hydrophilic head, and intermediate (i.e. connector) groups. Anionic sulfate and sulfonate head groups are the most common. Sulfates are limited to lower temperature applications because of their susceptibility to hydrolyze above about 60 °C. Appropriate hydrophobe lengths (typically from 12 to 16 carbon atoms) have been found to depend on the effective alkane carbon number (EACN) and other factors (e.g. aromaticity) of the crude oil (Aoudia et al., 1995). Shortening hydrophobes decreases their affinity for an oil phase resulting in greater salinity tolerance; however, this may reduce the benefits of oil solubilization (Bourrel and Schechter, 1988). Branched hydrophobes reduce packing at the oil/water interface, forming less ordered microemulsion structures of lower viscosity and free from highly viscous gel, liquid crystal, and/or macroemulsion formations (Levitt et al., 2006; Bourrel and Schechter, 1988). Low viscosity microemulsion has good transport through porous media, which can provide a low pressure gradient and reduced surfactant retention in the reservoir (Levitt et al., 2006). Using multiple surfactants with different hydrophobe structures can also provide this low viscosity benefit by increasing chemical disorder among surfactant interactions. Recent research by Walker et al. (2012) showed that increasing temperature of surfactant mixtures helps recover oil in core floods by lowering both oil and microemulsion viscosity. Liu et al. (2008) has also shown that surfactant mixtures are aqueous stable at higher electrolyte and divalent cation concentrations

compared to containing a single surfactant. Intermediate groups connecting the hydrophobe to the head group can be beneficial in providing stability at the water/oil interface of a microemulsion droplet. The number of groups and their polarity greatly affects tolerance to salinity and hardness. An ethylene oxide (EO) group is a common polar, intermediate group with high tolerance to salinity and hardness. One or more EO can vastly increase tolerance to salinity and hardness (Austad and Milter, 1998; Bourrel and Schechter, 1988; Aoudia et al., 1995; Hirasaki et al., 2004).

Alkali

Alkali in chemical flooding is beneficial for in-situ soap generation (i.e. saponification) from reactive crude oil components and reducing anionic surfactant adsorption on rock surfaces (Nelson et al., 1984). In situ saponification essentially provides free chemicals to reduce IFT, while low adsorption maintains surfactant slug propagation through the reservoir (Nelson and Pope, 1978; Falls et al., 1994; Zhang and Hirasaki, 2006). Sodium carbonate (Na_2CO_3) is the alkali agent most commonly discussed in the literature, although sodium hydroxide (NaOH) and the more novel sodium metaborate have also been discussed.

Sodium carbonate is an inexpensive alkali agent shown to provide in situ saponification, reduced surfactant adsorption, reduced co-solvent requirements, and lower microemulsion equilibration time. However, one disadvantage of sodium carbonate is the precipitation of calcium carbonate (CaCO3) when used in the presence of hard brine containing calcium ion (Ca^{++}) (Labrid, 1991). To minimize and/or prevent precipitate formation, source water can be softened and/or de-salinated to lower the concentrations of calcium and other divalent ions. A novel alternative may be sodium metaborate ($NaB(OH)_4$), which is an alkali metal borate that sequesters the calcium

(Ca^{++}) and magnesium ions (Mg^{++}). Flaaten et al. (2008) and Zhang et al. (2008) describe how metaborate tolerance to Ca^{++} and Mg^{++} is much greater than sodium carbonate. Additionally, Zhang et al. (2008) shows sodium metaborate to outperform sodium carbonate in enhanced imbibition experiments in silica and carbonate rocks. Metaborate chemistry shown by infrared and ion exchange studies depends on concentration and solution pH (Anderson et al., 1964; Ingri, 1963; Filippova et al., 1975). The monomeric form $B(OH)_4^-$ is most stable at high pH (> 10.5) common for ASP applications. This form is a classic alkaline buffer in detergent formulations, with pH determined principally by the acid-to-base ratio as shown:

$$H^+ = K_a \frac{B(OH)_3}{B(OH)_4^-}$$

A lower pH range of about 5 to 10.5 gives several polymeric borate ion species ($B_5O_6(OH)^{4-}$, $B_3O_3(OH)^{4-}$, $B_4O_5OH^{4-}$, $B_3O_3(OH)_5^{2-}$), although nonionic borate, $B(OH)_3$, is the dominant species when pH is less than 7 (Anderson et al., 1964; Filippova et al., 1975; Ingri, 1963).

Polymer

Polymer in chemical flooding is beneficial for mobility control, and to achieve an even, piston-like displacement process. The addition of a high molecular weight water-soluble polymer to a surfactant slug increases the viscosity, which is necessary to offset the increase in the aqueous relative permeability that occurs when the IFT is reduced by 1000s of fold. The higher viscosity also lowers the mobility ratio, which can increase the sweep efficiency in a reservoir by preventing an unstable displacement (fingering), channeling caused by layering and other heterogeneities, and bypassing among other mechanisms. Therefore, polymer is necessary in both the surfactant slug and the polymer drive pushing the slug.

Hydrolyzed polyacrylamides (HPAMs) are a common, inexpensive class of polymers containing long, flexible structures (Sorbie, 1991; Lake, 1989; Wreath, 1989). The length of the polymer structure can be selected based on reservoir permeability and other rock characteristics such as pore structure but generally lower permeability means a lower molecular weight polymer must be used. A comprehensive overview of polymers in chemical EOR can be found in Sorbie (1991), and a recent study of polymers in challenging (high temperature, high salinity) environments can be found in Levitt (2009).

Flaaten et al. (2008) describes the preparation process of the Flopaam® 3330S polymer by SNF. Flopaam® 3330S is a 30% hydrolyzed polyacrylamide (HPAM) with a molecular weight of 8 million Daltons. Prior to preparation, polymer exists as a dry powder, which is used to initially prepare a concentrated stock solution. A concentrated stock solution is prepared by slowly sprinkling dry polymer into a continuously stirred low-salinity (~1000 ppm TDS) aqueous solution. Stock solutions generally have a polymer concentration 4-8 times what is needed for various laboratory experiments (phase behavior, core floods, etc.), with 5,000 to 10,000 ppm being common. A stock solution is slowly mixed for a period of 1 to 2 days to properly hydrate the dry powdered polymer. To ensure proper hydration, stock solutions must have an acceptable filtration ratio following filtration through a 1.2 um filter. Filtration ratio compares the time to filter equal volumes of polymer solution near the beginning and end of filtration, with an acceptable filtration ratio being less than 1.2.

For a given temperature, polymer viscosity is heavily dependent on polymer concentration, salinity, and hardness of a solution. Polymer concentrations used in surfactant slugs and/or polymer drives generally range from 1,000 to 3,000 ppm, which usually provides sufficient viscosity in core flood applications for average rock permeability (~50-500 md) and oil viscosity (~1-10 cp). Polymer tolerance to salinity and

hardness can vary dramatically, as shown in Flaaten et al. (2008). To determine HPAM tolerance to salinity and hardness, the viscosity of HPAM polymer mixtures containing various concentrations of hard and soft brine was measured at 11 sec^{-1} and 23 C using a couette-type viscometer. Figure 5 shows the viscosity data for mixtures containing hard and soft brines with 2000 and 1500 ppm HPAM, respectively. Both viscosity curves decrease sharply as salinity increases to about 40,000 mg/L TDS. At salinity greater than 40,000 mg/L TDS, hard and soft brine mixtures have roughly constant viscosity of 4 and 6 cp, respectively, which demonstrates the ability of HPAM to maintain viscosity at extremely high salinity and hardness. The long, branched structure of a polymer molecule will collapse and coil as salinity increases, reducing its intertwining with neighboring polymer molecules to ultimately lower viscosity. Divalent Ca^{++} and Mg^{++} in hard brine are smaller and of greater ionic strength than monovalent Na^{+}, and more effectively collapse a polymer molecule. For a relatively light oil applications (e.g. 1-2 cp) with hard, saline brine, an HPAM solution with a four centipoise viscosity provides acceptable mobility control, and therefore eliminates the need for soft water.

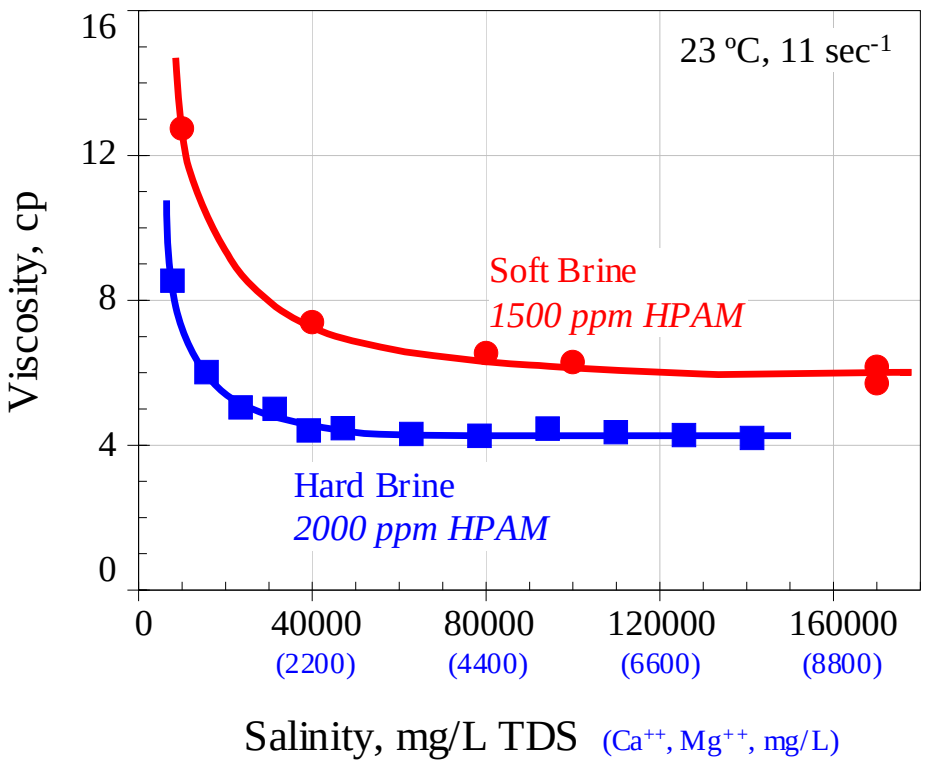

Figure 5: Viscosity curves using Flopaam® 3330S polymer in hard or soft brine

Co-solvent

The purpose of co-solvents are to introduce a small molecular weight compound to act at the oil-water interface, get between the surfactant hydrocarbon groups, and reduce the viscosity of the oil/water microemulsion (Sanz and Pope, 1996). These co-solvents have been shown to reduce gel formation, microemulsion viscosity, and microemulsion equilibration time. An alcohol co-solvent that is equally soluble in oil and water or has a partition coefficient between the oil and water of one (neutral) has been found to perform well. Propyl, butyl, and pentyl alcohols are generally closest to neutrality, and have therefore been used the most in the past 40 years. However, some disadvantages of adding alcohols to surfactant slugs are a decrease in the optimal

solubilization ratio, an increase in the IFT, and an increase in the chemical cost; however, the advantages of using alcohol can sometimes outweigh the disadvantages. Ethylene glycol monobutyl ether and other glycols also make good co-solvents and have some advantages over light alcohols such as a higher flash point (Jackson, 2006). A recent study by Sahni et al. (2010) uses ethylene glycol monobutyl ether (EGBE), diethylene glycol monobutyl ether (DGBE), and triethylene glycol monobutyl ether (TGBE) as co-solvents. Their research showed the role of co-solvents an/or co-surfactants in making chemical floods robust, and help achieve clear, aqueous stable ASP slugs at optimum salinity (Sahni et al., 2010).

MICROEMULSION PHASE BEHAVIOR EXPERIMENTS

A successful laboratory approach to chemical flooding generally shows a chemical formulation (i.e. one or more surfactants, co-solvent, alkali, polymer, and electrolytes) having good microemulsion phase behavior performance when contacted with crude oil, and gives good recovery of residual oil in cores (Jackson, 2006; Levitt, 2006; Levitt et al., 2006; Flaaten et al., 2008). Winsor (1954) characterized these microemulsions containing surfactant, oil, and water as Type I (oil solubilized in water), Type II (water solubilized in oil), and Type III (middle phase, often assumed to be bi-continuous, and may be in equilibrium with excess oil and water phases). Figure 6 shows an example phase behavior experiment containing 2 wt% total surfactant (1.5 wt% $C_{16/17}$-7PO-SO_4^- + 0.5 wt% $IOS_{15/18}$) and 2 wt% co-solvent (sec-butanol) that transitions from Type I (left-most pipette with 4.1 wt% NaCl) to Type III (6^{th} pipette from left with 4.6 wt% NaCl) to Type II (right-most pipette with 5.0 wt% NaCl). Several chemical parameters can be varied to transition (i.e. shift) from a lower- to upper-phase (i.e. Type I to Type III to Type II) microemulsion and vice versa, to ultimately provide tolerance to

salinity and hardness (Winsor, 1954; Healy et al., 1976; Bourrel and Schechter, 1988; Aoudia et al., 1995; Green and Willhite, 1998).

Flaaten (2007) found that varying the total surfactant concentration has a relatively small effect on phase behavior performance. More surfactant will invariably solubilize more oil; however, the ratio of solubilized oil volume relative to surfactant volume (i.e. oil solubilization ratio) remains relatively unchanged. For field injection, a sufficient surfactant quantity will exceed adsorption requirements of the rock, and surfactant concentration will depend on the desired surfactant slug injection volume.

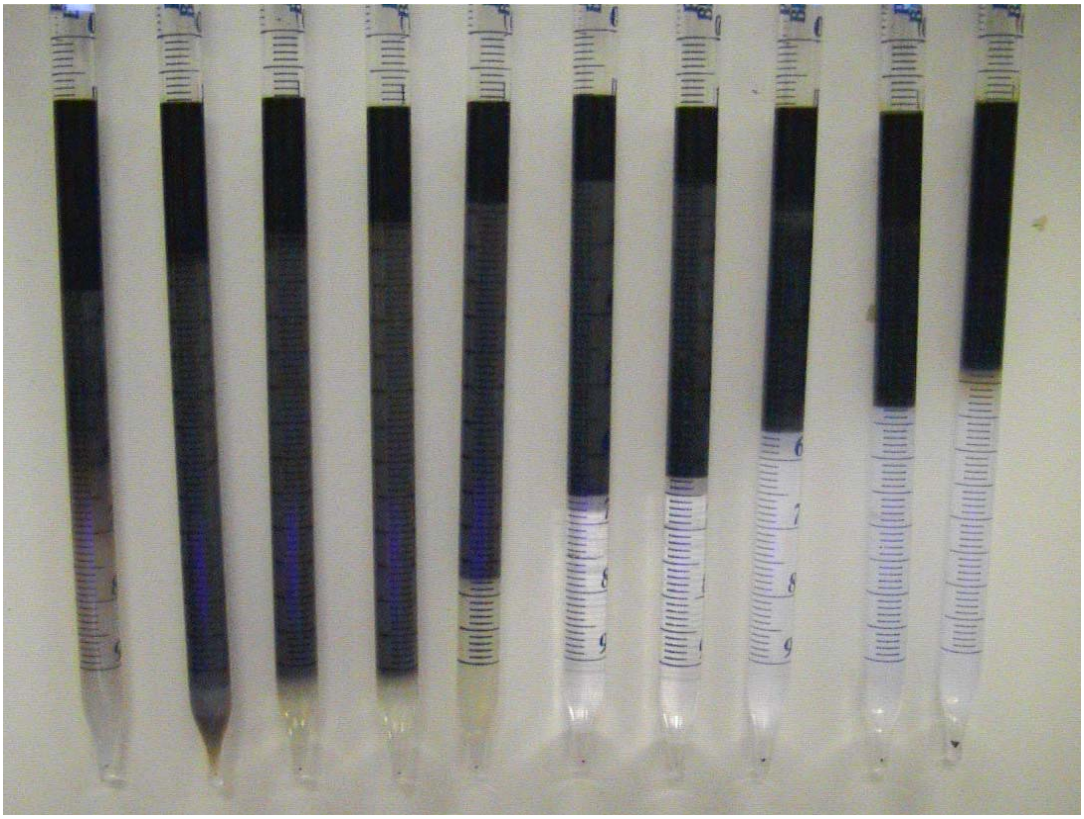

Figure 6: Phase behavior pipettes arranged from 4.1 (left) to 5.0 (right) wt% NaCl at 0.1 wt% increments, showing the microemulsion transition from Type I to III to II

Chemical formulations are initially screened and characterized with microemulsion phase behavior experiments, and must pass several screening and performance criteria (for microemulsions at or near optimal salinity) to be considered for a core flood. A desired microemulsion must be of low viscosity, appear free of liquid crystals, equilibrate quickly (usually less than 7 days), and have sufficiently high solubilization ratio (greater or equal to 10 for IFT lower than about 0.003 dynes/cm). Healy et al. (1976) provides a method for calculating the solubilization ratio. For a phase behavior pipette at a particular salinity value, volumes of oil (Vo) and water (Vw) solubilized in the microemulsion phase can be measured, and subsequently normalized to the total pure surfactant volume (Vs) present to find the oil and water solubilization ratios, or Vo/Vs and Vw/Vs, respectively. The assumption for this calculation is that all the surfactant is present in the microemulsion phase, rather than in either pure oil or water phases. Measuring and calculating oil and water solubilization ratios for pipettes over a range of Type I, II, and III salinity values can provide enough information to interpolate an optimal salinity and solubilization ratio. Interpolation is generally estimated visually, assessing the point where curves drawn through oil and water solubilization ratio data intersect (though more mathematically rigorous methods could be used). Although low IFT can be assessed by visually tilting the pipette, interpolation matters in that obtaining an optimal solubilization ratio provides a quantitative value at which to easily screen a formulation without having to directly measure IFT (which is more time-intensive). Figure 7 shows curve fitting of oil and water solubilization ratio data plotted versus salinity, with the intersection point of the two curves representing a Type III microemulsion with an optimal solubilization ratio (σ^*) and optimal salinity (S^*) value.

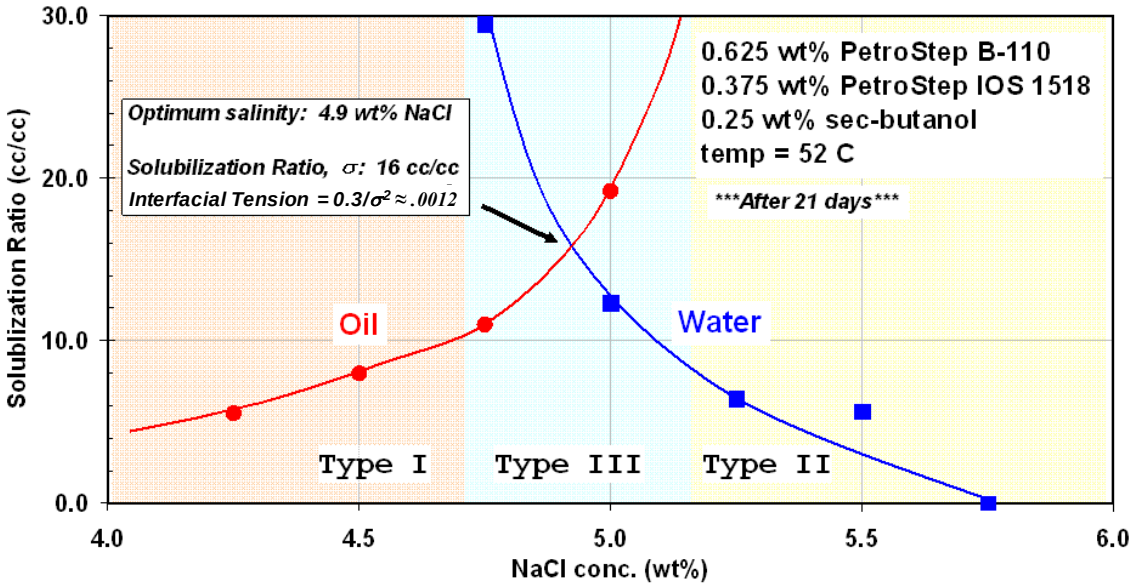

Figure 7: Oil and water solubilization ratio curves in Types I, II, and III salinity regions.

Huh (1979) noted a correlation between the solubilization ratio at optimal salinity, σ^*, and IFT, γ, according to the relationship equation $\gamma = 0.3/(\sigma^*)^2$. Because of the inverse relationship between σ^* and IFT, the higher the σ^* value is, the lower the IFT. A low IFT value is important when considering the effect of the capillary number, N_C, on residual oil saturation. The capillary number is a non-dimensional parameter relating viscous forces to capillary forces that is expressed as: $N_C = k\nabla|\Phi|/\gamma$, where $k\nabla|\Phi|$ is the viscous potential gradient. The capillary number is inversely proportional to the IFT, and therefore a low IFT gives a high capillary number. When the capillary number becomes sufficiently high, residual oil saturation begins to decrease towards zero, enabling a greater amount of mobile oil (Shen et al., 2006). Delshad et al. (1986) showed this in untreated Berea sandstone core, where from N_c = 10^{-5} to 10^{-3} residual oil saturation declined from an initial value of about 0.32 to zero.

Laboratory Procedure

Laboratory phase behavior screening is a quick, inexpensive procedure that can make chemical formula design an efficient process. Phase behavior experiments are usually prepared using Fisherbrand® standard 5 mL borosilicate serological pipettes (5 mm inner diameter and 0.1 mL markings) into which 2 mL total aqueous (chemical formulation) volume of various concentrated stock (surfactant, co-surfactant, co-solvent, alkali, and hard or soft brine) solutions are dispensed, followed by 1 mL of crude oil. An experiment uses an array of pipettes with incrementally different salinities to identify microemulsion type (i.e. Type I, II, or III) versus salinity, and hence optimal salinity. Coarse salinity increments could initially identify the general optimal salinity region, with additional finer incremented experiments providing more accuracy. Aqueous stability is assessed before adding crude oil to visually detect any non-homogeneity (e.g. phase separation, precipitation, or cloudiness) in the aqueous phase. Non-homogeneity at and slightly beyond optimal salinity would fail this screening because of potentially unstable injection solutions, which are commonly at optimal salinity. Polymer is generally absent in phase behavior experiments, and therefore identical aqueous volumes containing polymer are prepared in 10 mL glass vials to assess aqueous stability with polymer. Clear, homogeneous, and single-phase solutions are often validated and confirmed visually under ultraviolet light, and occasionally using centrifugation if suspended precipitates are suspected. Pipettes containing crude oil and a stable aqueous phase are heat-sealed, cooled, slowly inverted 12 to 15 times for oil and aqueous phase mixing, and then incubated in a convection oven at reservoir temperature. Water-microemulsion and/or microemulsion-oil interfaces are recorded over time to the nearest 0.01 mL (using interpolation with 0.1 mL markings), and are used to calculate solubilization ratio curves, optimal salinity, and solubilization ratio at optimal salinity.

Pipettes are periodically tilted to qualitatively inspect the fluidity and viscosity of the microemulsion, and to screen against deleterious macroemulsion, gel, and/or liquid crystals.

Relevance to reservoir-to-market modeling

Laboratory phase behavior experiments tend to provide only part of the information for a reservoir-to-market model, with further value coming from core flood experiments and simulation studies. However, specific details for the coreflood are ultimately obtained from information gained from phase behavior experiments, and therefore phase behavior success essentially provides the path for further experimentation. The following subsections will elaborate on useful information that may be obtained from phase behavior results including: salinity and/or hardness tolerance, chemical types and/or brands, chemical effectiveness, and chemical concentrations among other things.

Salinity and/or hardness tolerance

A chemical formulation is usually designed to handle, as best as possible, for the salinity and hardness of available source water. However, the salinity and/or hardness of available source water may exceed concentrations for optimal performance, and techniques such as softening or de-salination must be considered. Softening/de-salination usually requires a capital expense for the equipment and/or operating expenses to run the equipment. An alternative approach would be to incur a capital expense for drilling/completing a water source well in a less hard, less saline zone, or incurring operating expenses for obtaining source water from other external sources. Alternatively, chemicals tolerant of hard, saline conditions may avoid the need for water softening/de-salination; however, these chemicals may have limitations of their own (e.g. decreased

performance, limited commercial availability, and/or higher chemical expenses) that ultimately pose an economic tradeoff.

Chemical types and/or brands

Although many different chemical types (e.g. structures) and/or brands exist, not all of them can be easily manufactured on a commercial basis. Commercially available surfactants tend to be much cheaper and may have greater availability in the large volumes required for a field-scale chemical EOR project. The supply and cost of novel chemicals with limited or no large-scale commercial availability must be considered, despite their ability to perform well in phase behavior experiments. Additionally, the consistency and repeatability of surfactant production between small batches created for laboratory experiments and large-scale continuous surfactant production for commercial chemical flood purposes must be ensured (Zhao et al., 2010). A reservoir-to-market model will characterize chemical inputs with a unit cost, which ultimately translates into operating expenses when calculating cash flows. If novel chemicals perform well and are selected, it must be determined early on if they will have a premium cost and are indeed available, rather than assuming more generalized, commercial chemical costs and unlimited availability.

Chemical effectiveness

The ability of a chemical formulation to effectively form a well performing, low IFT microemulsion mainly provides qualitative screening criteria, rather than a quantifiable metric for expected oil recovery. Screening for a solubilization ratio greater than 10 generally provides a sufficiently low IFT to reduce residual oil saturation to near zero based on the capillary number (Delshad et al., 1986). However, the degree to which additional mobile oil can be recovered from a reservoir is dependent on a variety of other

factors (chemical consumption, reservoir heterogeneity, etc.) not present in phase behavior experimentation. Further testing of chemical formulations in cores provides much more information on their ability to effectively recover oil from rock.

Chemical concentrations

Chemical concentrations used in phase behavior experiments can provide some information on the amount of chemicals that may be required for a chemical EOR project; however, this information may be limited. For example, phase behavior experiments can perform well over a range of surfactant concentrations. Lower surfactant concentrations will ultimately lower the project costs, but other factors such as surfactant adsorption on rock surfaces and surfactant loss caused by reservoir heterogeneity may dictate the concentration and total volume of surfactant used (which cannot be determined in phase behavior experiments alone). Polymer concentration may be determined more easily because it can be tested in the laboratory given a desired viscosity and known source water salinity/hardness among other things. Furthermore, determining whether alkali will be used can reduce the amount of planned surfactant, even if it is a rough estimate.

CORE FLOOD EXPERIMENTATION FOR SCREENING CHEMICAL FORMULATIONS

Chemical flooding in cores is a quick, efficient method for validating performance of chemical formulations showing low IFT in phase behavior experiments. Core flooding generally involves a basic flooding sequence, which includes a surfactant slug followed by a polymer drive. Core flood performance can be evaluated on residual oil recovery, surfactant retention, pressure gradient, salinity gradient, and other technical parameters. As referred to previously, mobilizing residual oil for recovery in a core flood is

dependent on the formulation tested in phase behavior to show low oil/water IFT. Core floods are the preliminary and necessary step prior to an actual field pilot, and therefore provide a prediction and/or expectation of pilot performance. The candidate formulation selected for a pilot is ultimately what provides good performance in core floods.

SALINITY GRADIENT IMPORTANCE

Using a negative salinity gradient in chemical flooding can ensure a robust design that captures the low IFT, optimal salinity region for the best possible performance. As mentioned previously, optimizing the electrolyte strength (i.e. optimal salinity) of the surfactant slug for core flood experiments is a crucial design criterion for achieving ultra-low IFT in the salinity region of a Type III microemulsion. Phase behavior microemulsion volumes experience IFT at oil-microemulsion and/or water-microemulsion interfaces (depending on Type I, II, or III), each having different IFT values. However, a Type III microemulsion specifically at optimal salinity is unique and favorable because both interfaces have equal and low IFT. Salinity greater than optimal lowers oil-microemulsion IFT and can trap microemulsion with the residual oil on the rock while a greater water-microemulsion IFT makes oil mobilization difficult. Salinity less than optimal keeps surfactant in microemulsion with the water phase via low water-microemulsion IFT, but minimizes oil mobilization with higher oil-microemulsion IFT. Additionally, designing for an unchanging optimal salinity is difficult for many reasons such as cation exchange, cross-flow mixing, and others. Pope et al. (1979) found a negative salinity gradient offers a robust chemical flood design, where initial formation brine exists at Type II salinity, and steps down to a surfactant slug at optimal salinity, followed by another step down to a polymer drive at Type I salinity. This helps counteract the dispersion for a finite surfactant slug process, and significantly increases

the probability of low IFT, Type III conditions somewhere in the mixing zone (of the surfactant slug), while ensuring a Type I salinity polymer drive for re-mobilization of surfactant into the water phase (Hirasaki et al., 1983; Levitt et al., 2006).

LABORATORY PROCEDURE

Chemical flooding in cores begins with a specific procedure for core preparation. To prepare cores from a block of rock, a core is drilled, cut, and dried, with typical core dimensions being 30 cm in length and 5 cm in diameter. Field cores from downhole core sampling can also be used, and several shorter lengths of core can be stacked upon each other to render a 30 cm total length. Cores are generally screened using air mini-permeameter measurements (at inlet, outlet, and middle) for undesirable heterogeneity and/or low permeability. Suitable dry cores are first fastened with plastic end pieces using quick-curing epoxy then encased within a thin, 6.5 cm diameter lexan tube filled with slow-curing epoxy. Two pressure taps are drilled 10 cm from each core face, and nylon flow lines epoxied into place. The core is fitted with valves, and pressure tested to 100 psi in a water bath for leaks. Cores are saturated with CO_2, evacuated with a vacuum pump, and then saturated with brine. A sequence of pre-chemical floods (brine, oil, and water floods) on a vertical core provides core data and residual oil saturation conditions. Brine first is flooded at a constant rate to measure the brine permeability from the steady-state pressure data. A constant rate, high pressure gradient (20 to 50 psi/ft) oil flood using filtered (1.2 um) crude oil is performed until steady-state (i.e. residual water saturation), followed by a low flow rate water flood (1 to 2 ft/day frontal velocity) using synthetic formation brine (SFB) until steady-state (i.e. residual oil saturation). Pressure and flow rate data provide end-point relative oil and water permeability values and residual saturation values, which help calculate design parameters such as apparent fluid viscosity

for mobility control. Core preparation has finished when water flooding renders residual oil saturation, and initial saturation with SFB.

Chemical flooding typically involves injection of a surfactant slug followed by a polymer drive. Surfactant slug volumes are generally about 0.2 to 0.4 pore volumes (PV), and polymer drive volumes are 1 to 2 PV or whatever volume completes the recovery of oil. In some cases, a pre-flush prior to the surfactant slug may be used to enable a favorable salinity gradient during the chemical flooding process. The injection sequence ultimately leads to four different recovery periods, which are characterized as: formation brine, oil bank, early post-surfactant breakthrough, and late microemulsion (Flaaten et al., 2008). After the start of surfactant slug injection, formation brine recovery is simply the SFB from the water flood and can typically last from 0.3 to 0.5 PV. An oil bank follows for about 0.5 PV, which is often characterized by a high oil cut (~30 – 50%) without any surfactant, and Type II salinity. Surfactant breakthrough occurs after about 0.8 PV have been injected, though early surfactant breakthrough can occur around 0.5 PV (or even earlier). Early post-surfactant breakthrough recovery is typically characterized by declining oil cut, Type III salinity, and recovery of microemulsion and surfactant. A late microemulsion recovery phase typically contains very low oil cut, and recovery of Type I salinity microemulsion that is almost all polymer drive. An accurate measurement of oil recovery requires “breaking” microemulsion into oil and water phases by either heating to 70 °C overnight (to hydrolyze sulfate surfactants) or diluting with de-ionized water. Successful core flood criteria include: high oil recovery (low final residual oil saturation), low surfactant retention (preferentially less than 0.2 mg surfactant/g rock) to reduce surfactant cost, and low pressure gradient.

IMPORTANT CHEMICAL EOR PARAMETERS FOR RESERVOIR-TO-MARKET MODELING

Building even a basic reservoir-to-market model for a potential chemical EOR project requires knowledge of several input parameters specific to the chemical EOR opportunity of interest. The basic categories used to build a reservoir-to-market model were discussed previously, and include defining the reservoir, well patterns, well performance, facilities (including pipes), rigs, schedule, and costs. For a mature field under water flood, several of these categories can be defined from the existing field data. Reservoir volumetrics and well patterns (e.g. five-spot) can be fairly well understood, and rigs for drilling new wells may not be needed if wells currently exist. Screening of the wells is quite definitive of the well status, well conditions, well integrity conditions of the cement and tubing, and criteria for injectivity or selective injectivity. New facilities construction and pipe replacements are common for a chemical EOR project, given the necessity of chemical mixing and injection, source water treatment, emulsion processing, and replacing old, often corroded pipelines; however, these activities are generally not unique to flooding projects or in particular for chemical EOR projects. Important input parameters generally defined uniquely for a particular chemical EOR project include well performance, materials, and source water among others, whose importance will be discussed in this work.

Defining well performance in a reservoir-to-market model determines the expected injection/production rates, and general economics (cash flow, NPV, etc.) associated with fluid streams. Higher expected rates increase the design of facility capacities and define Capex investment and Opex budget requirements (i.e. higher facilities Capex), larger Opex with injection fluid treatment/mixing and produced fluid processing, and higher revenues from produced oil among others. Well performance can be defined from simulation output, or well history data from analogue fields. However,

given that production performance in chemical EOR is heavily dependent of several factors (e.g. reservoir and fluid properties, chemical formulation performance), it is important to describe well performance according to the field of interest.

Defining chemical materials and source water inputs in the reservoir-to-market model are also very important, as they also depend heavily on specific properties for the field of interest. Opex for chemical and source water inputs is a highly sensitive and significant cost to project economics, and therefore must be defined as accurately as possible for a reservoir-to-market model to be credible and representative. The chemical formulation design process described previously showed how laboratory experiments can help optimize chemical concentrations, and use available source water. What-if scenarios that focus on minimizing chemical concentrations and using available water, even if extremely hard and saline, begin at the laboratory, and can vastly improve project field development plan and economics, and therefore should be accurately described and captured in a reservoir-to-market model.

CASE STUDY: LABORATORY PHASE BEHAVIOR AND CORE FLOOD SCREENING AND MODELING OF NOVEL CHEMICALS, SURFACTANT STRUCTURES, AND STRATEGIES FOR CHALLENGING ENVIRONMENTS

Flaaten et al. (2008) described in detail the process for screening a chemical formulation for a hard, saline environment using microemulsion phase behavior and core flood experiments. Novel chemicals are chosen for their ability to perform well in hard, saline brine, with the objective of reducing or eliminating the need for softening or reducing the salinity of water. Divalent cations can form deleterious precipitates with the conventional alkali sodium carbonate, and high salinity can reduce polymer viscosity among other things. This case study demonstrates some of the strategies used in

designing a successful chemical formulation, and some important considerations for managing the ranges of chemical flood uncertainty.

Hard, saline brine was a design challenge for a brine that contained about 157,000 mg/L total dissolved solids (TDS), 8700 mg/L of which were divalent Ca^{++} and Mg^{++} (based on actual reservoir formation brine composition data). Table 1 shows the composition data of the hard, saline brine. This brine was the aqueous medium for all phase behavior and core flood experiments, being used to saturate or water flood cores, and for phase behavior experiments, surfactant slugs, and polymer drive solutions. Experiments also used light crude oil obtained from a sandstone reservoir at a bottomhole static temperature of 52 °C. Crude density and viscosity at reservoir temperature were 0.8 g/cc (45^{o} API) and 1.96 cp (at 11 sec-1), respectively, compared to hard brine values of 1.1 g/cc and 0.73 cp.

Table 1: Composition of hard, saline brine (with high TDS) used in phase behavior and core flood experiments (Flaaten et al., 2008).

Ion	Na^{+}	Ca^{++}	Mg^{++}	Cl^{-}	Total Dissolved Solids
Concentration (mg / L)	51288	6648	2019	96570	156525

MATERIALS

Alkali, surfactant, and polymer chemicals were selected that would perform well in hard, saline environments, and therefore reduce or eliminate the need for soft water. Because this was a low temperature, light oil application, high performance surfactants were selected that had previous success in lower salinity environments and combined with surfactants capable of withstanding high salinity and hardness. Levitt et al. (2006), Jackson (2006), and Flaaten (2007) reported that a mixture of an alcohol propoxy sulfate

($C_{16/17}$–7PO–SO_4^-) and an internal olefin sulfonate (C_{15-18}IOS) showed high performance for several light oils. The alcohol propoxy sulfate contains a C_{16-17} branched alcohol hydrophobe, seven propylene oxide (PO) groups, and a sulfate group. Additionally, an alcohol ethoxy sulfonate (C_8–3EO–SO_3^-) with a C_8 branched hydrophobe was selected to tolerate hard, saline brine because of its three hydrophilic ethylene oxide (EO) groups. Combining surfactants can improve their individual performance in several significant ways including increased aqueous solubility and hardness tolerance. Also, adding co-solvents such as sec-butanol (SBA) and/or iso-butanol (IBA) can provide additional benefits of reducing microemulsion equilibration time and viscosity, assisting surfactant compatibility with polymer, and minimizing other aqueous stability problems (Pope et al., 1982; Sanz and Pope, 1995). Co-solvents are frequently small carbon chain (C_3 to C_5) alcohol molecules of neutral partitioning coefficient capable of acting at oil-water interfaces. Among other things, co-solvents can help reduce equilibrium time, which is the length of time an oil/water/surfactant mixture takes to form a constant volume, thermodynamically stable microemulsion phase (with “fast” equilibration generally taking less than 7 days).

Sodium metaborate ($NaB(OH)_4$) as a novel alkali gives pH values around 11 for 10,000 mg/L concentrations, sufficient for chemical flooding. The monomeric borate ion ($B(OH)_4^-$) provides alkaline buffering at high pH according the acid-to-base relation shown previously. Additionally, high tolerance to Ca^{++} and Mg^{++} increases metaborate solubility in hard brine, allowing ASP formulations using hard brine. The conventional alkali sodium carbonate (Na_2CO_3) at 10,000 mg/L concentration also gives a pH value around 11; however, it can only be used with soft water.

EXPERIMENTATION

Phase behavior experiments showed several chemical formulations having good phase behavior. Mixtures of an alcohol propoxy sulfate ($C_{16/17}$–7PO–SO_4^-) and an internal olefin sulfonate (C_{15-18}IOS) showed high solubilization ratios, and the addition of alcohol ethoxy sulfonate (C_8–3EO–SO_3^-) showed optimal salinity to increase. Table 2 and Figure 8 show the effect, and in this case trade-off, of adding higher proportions of alcohol ethoxy sulfonate on solubilization ratio and optimal salinity. The use of metaborate as a novel alkali was shown to provide good phase behavior performance even in the presence of concentrations of divalent cations. Table 3 lists phase behavior experiments that were performed with and without the novel alkali metaborate, with Figure 9 and Figure 10 plotting the results of solubilization ratio versus salinity for these experiments. The performance of these chemical formulations was then further validated using core flood experiments with Berea sandstone cores (Flaaten et al., 2008).

Table 2: Effects of alcohol ethoxy sulfonate proportion on optimal salinity and solubilization ratio in phase behavior experiments (Flaaten et al., 2008).

Propoxy Sulfate C_{16-17} – 7PO-SO_4^- (mg/L)	IOS C_{15-18}IOS (mg/L)	Ethoxy Sulfonate C_8 – 3EO-SO_3^- (mg/L)	Co-solvent SBA/IBA (mg/L)	Optimal Solubilization Ratio, σ* (cc/cc)	Equilibrium Time at S* (days)	Optimal Salinity, S* (mg/L TDS)
2500	2500	0	0	18	21	30000
5000	5000	5000	10000	10	5	98000
4400	4400	6200	10000	6.6	5	127000

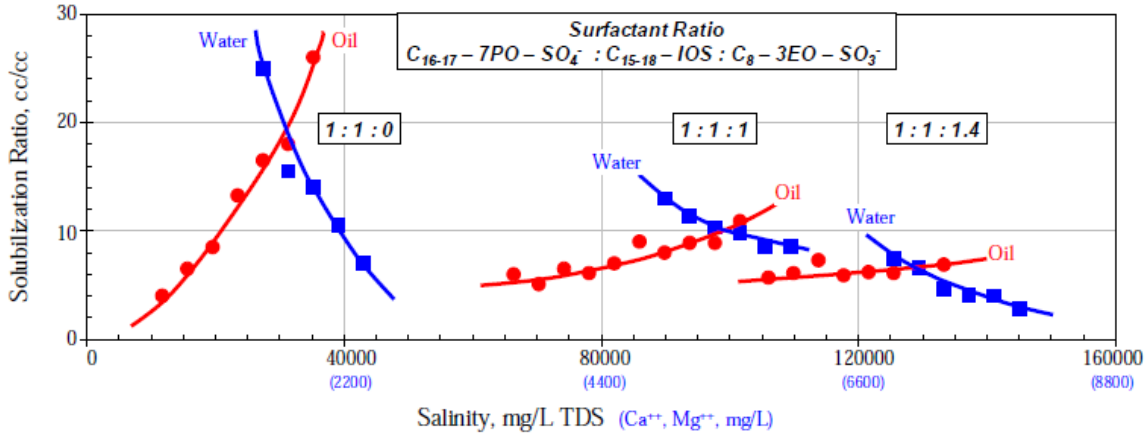

Figure 8: Effects of alcohol ethoxy sulfonate proportion on optimal salinity and solubilization ratio in phase behavior experiments (Flaaten et al., 2008).

Table 3: Phase behavior chemical formulations and results with and without the novel alkali metaborate (Flaaten et al., 2008).

Propoxy Sulfate C_{16-17} - 7PO-SO_4^- (mg/L)	IOS C_{15-18}IOS (mg/L)	Sodium Metaborate $NaB(OH)_4$ (mg/L)	Co-solvent SBA (mg/L)	Optimal Solubilization Ratio, σ (cc/cc)	Optimal Salinity, S* (mg/L TDS)
2500	2500	0	10000	18	30000
2500	2500	7500	10000	17	36000

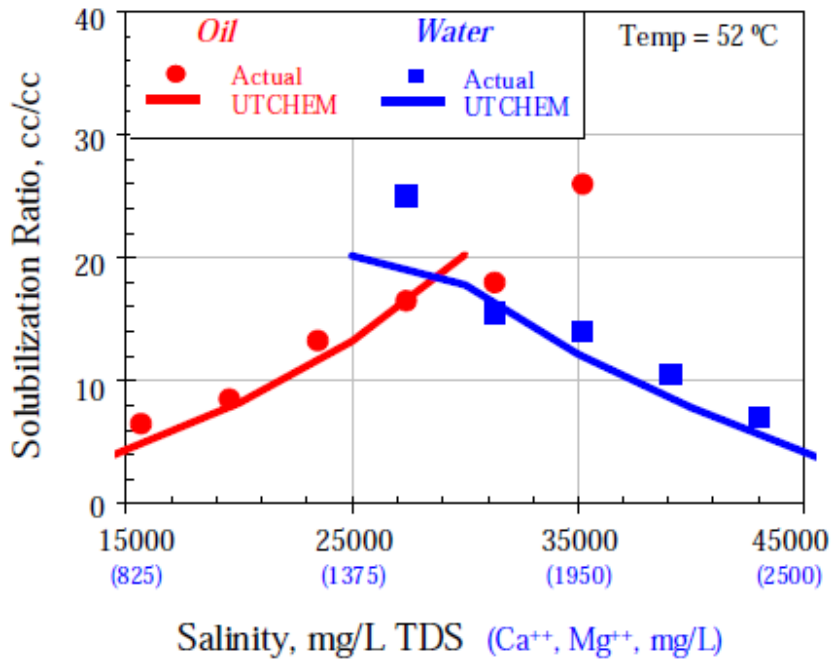

Figure 9: Phase behavior solubilization ratio versus salinity without novel alkali metaborate (Flaaten et al., 2008).

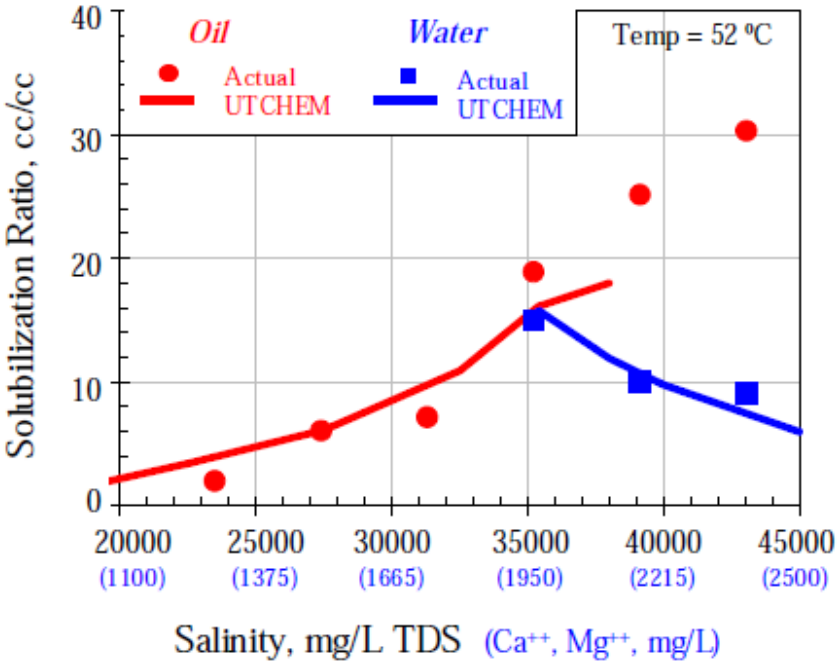

Figure 10: Phase behavior solubilization ratio versus salinity with novel alkali metaborate (Flaaten et al., 2008).

Core flood experiments helped validate chemical formulations performing well in phase behavior, and provide understanding with additional performance metrics such as oil recovery, salinity change, and pressure drop during the experiment. Chemical concentrations in surfactant slugs were designed similarly to phase behavior formulations at optimal salinity, except with the addition of polymer. Also, the polymer drive contains a similar polymer concentration as the surfactant slug, only with a lower salinity (approximately 60% the electrolyte strength as the surfactant slug). Prior to injection, surfactant slug viscosities measured from 4 to 6.5 cp and polymer drive viscosities from 4.5 to 8.88 cp for the four floods, respectively, which adequately exceeded apparent viscosity values (calculated from 1.92 to 3.1 cp) for mobility control. Injection rates ranged from 1.6 to 2.2 ft/d, roughly twice that for an average water flood (typically at around 1 ft/d), and were constant for each core. Core floods injected a 0.3 pore volume surfactant slug, with a polymer drive volume of 1.7 to 2.0 pore volumes depending on completion of microemulsion recovery (Flaaten et al., 2008).

Figure 11 and Figure 12 show oil cut and cumulative oil recovery results for core floods with and without novel alkali metaborate, respectively. Core floods rendered a cumulative oil recovery greater than 80%, which validates the ability of the chemical formulations to recover oil in cores. The specific changes in oil cut and recovery with time often depends on the effluent salinity, when surfactant breakthrough occurs, and what microemulsion type is recovered. Figure 13 and Figure 14 shows effluent salinity for the core floods with and without metaborate, respectively, versus pore volume time. For both scenarios, salinity decreases with time (i.e. negative salinity gradient), following the desired transition from Type II to Type III (slug) to Type I (polymer drive) phase behavior. For the core flood with metaborate, salinity did not drop to Type I conditions as

sharply as in the core flood without mataborate, resulting in higher oil cut later in the experiment (Flaaten et al., 2008).

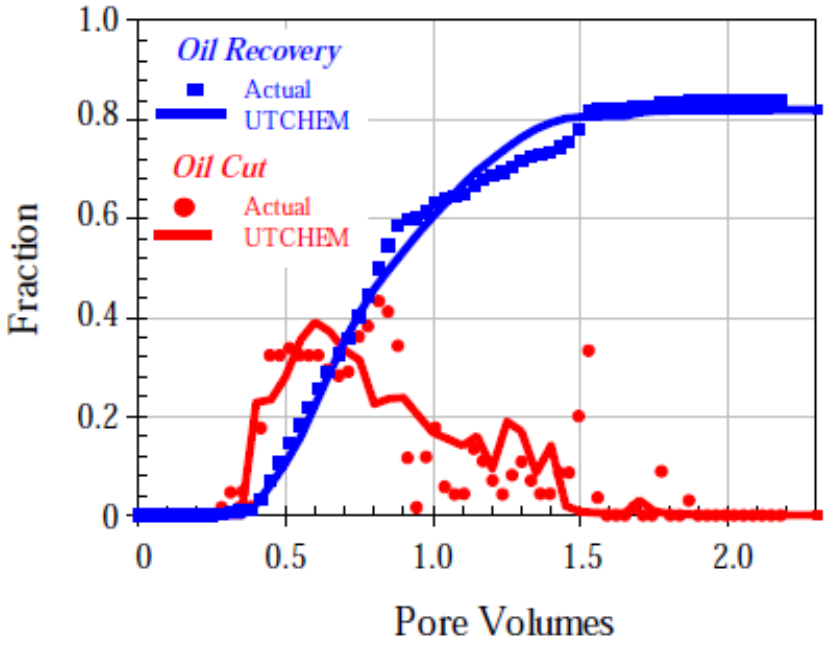

Figure 11: Oil cut and cumulative oil recovery for the core flood without novel alkali metaborate (Flaaten et al., 2008).

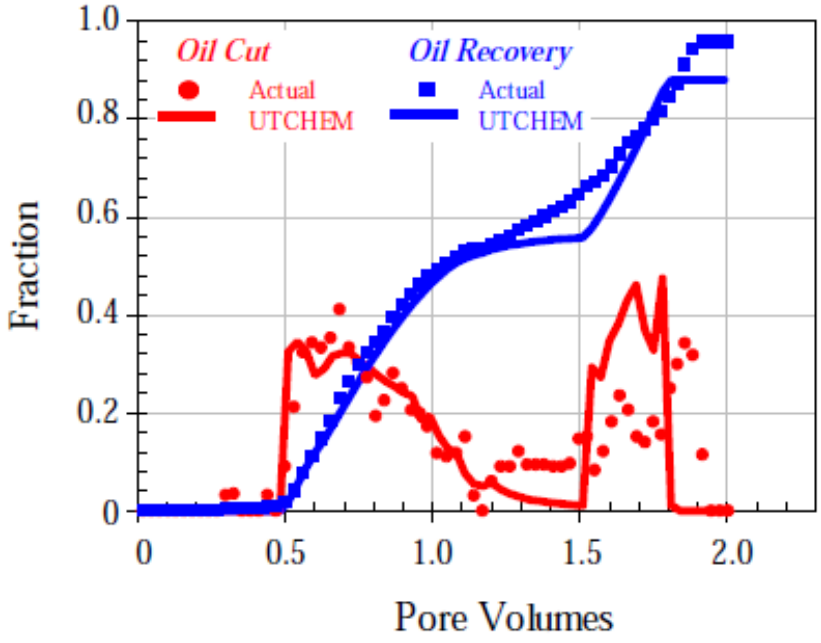

Figure 12: Oil cut and cumulative oil recovery for the core flood with novel alkali metaborate (Flaaten et al., 2008).

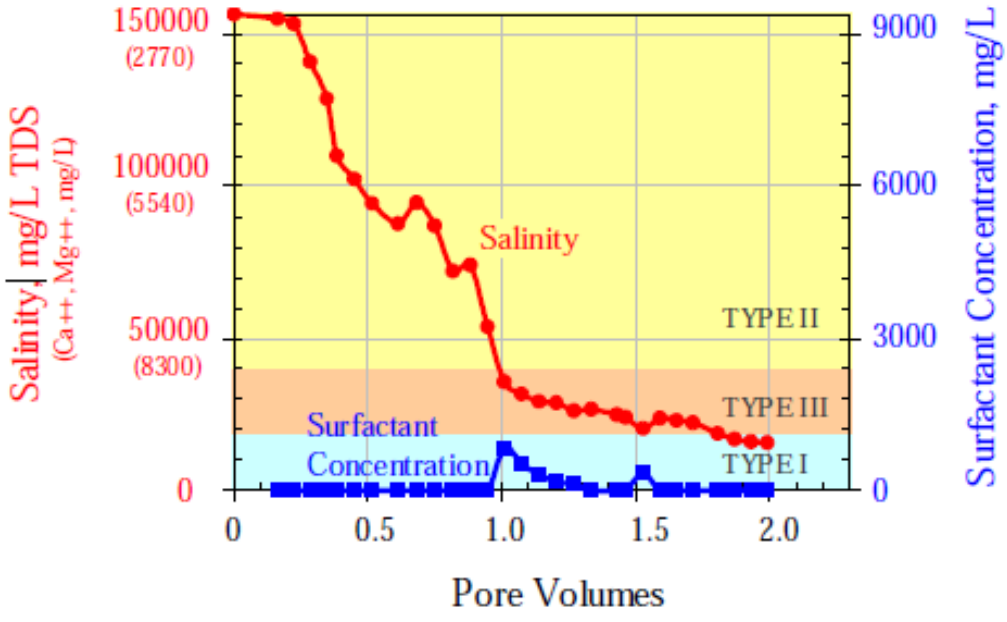

Figure 13: Effluent salinity and surfactant concentration for the core flood without novel alkali metaborate (Flaaten et al., 2008).

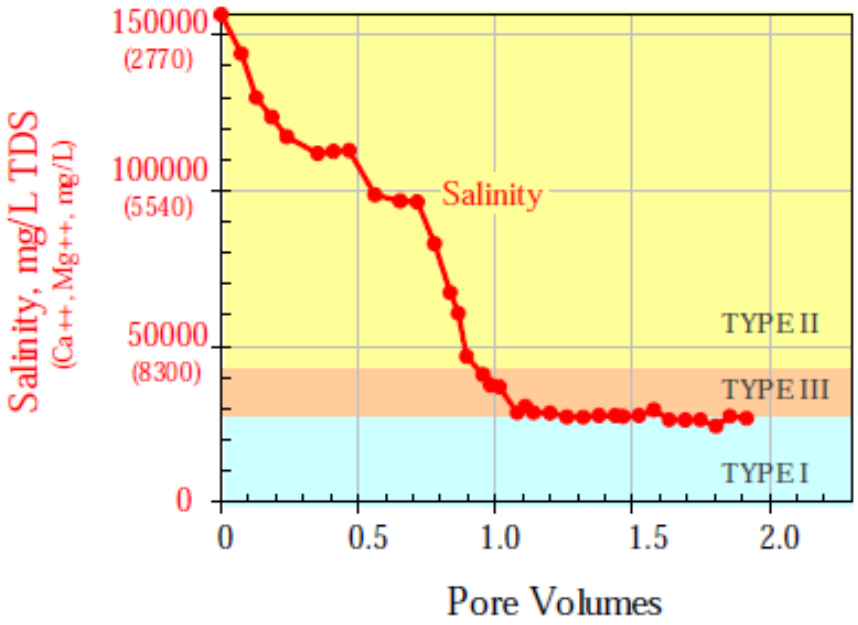

Figure 14: Effluent salinity for the core flood with novel alkali metaborate (Flaaten et al., 2008).

LABORATORY MODELING/SIMULATION ASPECTS TO DESCRIBE WELL PERFORMANCE

Well performance is a necessary input for a reservoir-to-market model, and, in the absence of field-scale well history from pilot or analogue data, a chemical flood simulator may be required to define the well performance. Core flood can provide calibration data for tuning/history matching a model in a chemical flood simulator. Mohammadi (2008) provides a comprehensive explanation of the UTCHEM chemical flood simulator, including work extending the simulator to include metaborate geochemistry. The UTCHEM simulator is a three-dimensional multiphase, multicomponent simulator useful for mechanistic modeling of chemical flooding at both the laboratory and field scales. Mechanisms such as surfactant phase behavior (Nelson and Pope, 1978; Satoh, 1984; Prouvost et al., 1984; Camilleri et al., 1987), three phase relative permeability (Delshad et

al., 1987; Delshad and Pope, 1989), oil de-saturation (Delshad et al., 1986; Delshad et al., 1996), well model (Saad et al., 1989), shear-thinning polymer viscosity (Wreath, 1989; Wreath et al., 1990), cation exchange with clay and micelle (Hirasaki, 1982; Bhuyan et al., 1990), tracer partitioning (Jin et al. 1995), and chemical reactions (Bhuyan et al., 1990; 1991) are included. Combining different modules in the simulator makes it a unique and multipurpose simulator. Bhuyan (1989) developed a geochemical model for alkali flooding. More recently, Mohammadi (2008) has used the simulator for modeling mechanistic ASP flooding. The phase behavior and core flood experimental data in Figure 9, Figure 10, Figure 11, and Figure 12 shows the use of UTCHEM for history matching (Flaaten et al., 2008). History matching experimental data calibrates the chemical flood model, which can then be scaled up to a field scale representative of the project of interest. Ultimately, field-scale simulation output can be used to describe well performance input in the reservoir-to-market model.

The simulation matches with UTCHEM has value for validating the forward modeling capability with laboratory experiments. The accurate predicting capability is then an important input to the reservoir-to-market model and the scenario building methodology. Laboratory simulation results and field analogue data from other pilot studies are the only data that can calibrate and/or validate the reservoir-to-market model until an actual field pilot is performed. Therefore, for early pre-pilot project screening during the concept selection phase, these laboratory simulations can be useful. Laboratory simulations can be upscaled to simulate a pilot or commercial-scale project, and well performance output can play a critical role in whether a reservoir-to-market model shows a project to be selected or not based on economic feasibility.

RECENT ADVANCES IN CHEMICAL EOR

Chemical EOR research has gained a lot of attention recently, and several novel advances have been successfully performed over the past couple of years. Several novel surfactant structures have been successfully tested that help broaden the reservoir conditions and crude oil properties at which chemical EOR would be possible. Correlations for predicting and optimizing surfactant structure and performance have also been developed. This section will describe these recent advances in chemical EOR research.

NOVEL SURFACTANT STRUCTURES

Several recent chemical EOR experimental studies have been performed using novel surfactant classes. Adkins et al. (2010), Adkins et al. (2012), and Lu et al. (2012) studied surfactants with Guerbet alcohol structures, which included both sulfate and carboxylate structures. Liyanage et al. (2012) successfully tested a novel surfactant with a Tristyrylphenol (TSP) hydrophobe derived on the petrochemical feedstocks phenol and styrene. These novel surfactants were tested in challenging conditions such as high temperature, high salinity and hardness, and heavy (e.g. high EACN), waxy, and/or high acid number crude oils among other things. They were found to give good performance, and aim to be cost effective.

Adkins et al. (2010) focused on inexpensive Guerbet alkoxy sulfate surfactants that are stable at high temperature and high salinity. Guerbet alkoxy sulfate surfactants are derived from inexpensive Guerbet alcohols, which are formed through dimerization of monomer alcohols. This can create a large, branched structure that is favorable for chemical EOR applications. Although Guerbet alcohols of high purity are expensive relative to other alcohols, the cost can be substantially decreased for less pure blends (85-

95% Guerbet alcohol and 5-15% monomer alcohol), while actually providing better performing surfactants due to the alcohol monomer forming co-surfactants (Adkins et al., 2010). Guerbet alkoxy sulfate surfactants can be tailored to specific reservoir conditions and crude oil properties by adding propylene oxide (PO) and ethylene oxide units to the Guerbet alcohol, followed by sulfation (Adkins et al., 2010). Additionally, Yang et al. (2010) describe using butylene oxide (BO) units on Guerbet alkoxy sulfates as well. Although sulfate surfactants, such as $C_{16/17}$-7PO-SO_4^- discussed previously, can hydrolyze at high temperatures, Guerbet alkoxy sulfate surfactants were found to be stable for years at temperatures of 85 C to 100 C over a specific alkalinity range (i.e. using concentrations of Na_2CO_3). Adkins et al. (2010) showed low IFT phase behavior and high oil recovery core flood experiments using a Guerbet alkoxy sulfate surfactant with the chemical formula C_{32}-7PO-14EO-SO_4^-. The formulation also contained C_{20-24}IOS as a co-surfactant, and TEGBE as a co-solvent among other chemicals.

Adkins et al. (2012) and Lu et al. (2012) show chemical EOR experimental results for Guerbet alkoxy carboxylate structures. Large Guerbet alkoxylates undergo carboxylation (carboxymethylation) to form these structures, with propylene oxide (PO) and ethylene oxide (EO) alkoxy groups commonly separating the Guerbet alcohol from the carboxylate of these anionic surfactants (Adkins et al., 2012). The advantage of Guerbet alkoxy carboxylate surfactants over Guerbet alkoxy sulfate surfactants is a tolerance of high temperature without the need of high pH maintained at 10-11, which was a condition for high temperature stability of Guerbet alkoxy sulfate surfactants (Adkins et al., 2012). Guerbet alkoxy carboxylate surfactants can also tolerate hardness. Therefore, other than the anionic head, the structure of the carboxylate and sulfate surfactants are nearly identical, with carboxylates providing an added benefit with tolerance to high temperature and hardness. Additionally, these carboxylates were found

to have a synergistic effect when used with internal olefin sulfonate (IOS) co-surfactants, which can further help lower the cost of a high performing surfactant mixture (Lu et al., 2012).

Liyanage et al. (2012) describe chemical EOR experimental results using Tristyrylphenol (TSP) as a novel hydrophobe for a surfactant structure. The success of TSP as a novel surfactant structure helps to diversify the raw material base for surfactants, and TSP specifically was found to perform well with crude oils that are waxy with a high acid number (Liyanage et al., 2012). Similar to the Guerbet alkoxy surfactants mentioned previously, TSP surfactants can contain a number of propylene oxide (PO) and ethylene oxide (EO) groups between the TSP hydrophobe and the sulfate anionic head.

RECENT CORRELATIONS FOR PREDICTION AND OPTIMIZATION

Solairaj et al. (2012b) and Solairaj (2011) developed novel correlations to predict the optimum surfactant structure for a chemical EOR application. The correlation predicts the mole average weighted carbon number of a surfactant mixture with respect to the hydrophobes. Parameters used in the correlation include the equivalent alkane carbon number (EACN), the mole average weighted propylene oxide (PO) and ethylene oxide numbers in the surfactant mixture, the temperature of interest (as well as a reference temperature), and the optimum salinity. Several conditions were used in developing the correlation, which included using a linear equation, characterizing the crude oil with the EACN parameter, using non-reactive crude oils, phase behavior data at optimum salinity, using mole fraction averages to describe surfactant mixtures, and not including co-solvent, divalent cations, nor hydrophobe branching in the correlation (Solairaj et al., 2012b). The correlation was specifically adapted to the novel types of surfactant

structures, and included mixtures of sulfate, sulfonate, carboxylate, and non-ionic surfactants. The overall objective was to reduce the time and cost for tailoring a surfactant mixture to a crude oil of interest, as well as to characterize the most important parameters affecting surfactant performance.

Another correlation was developed recently to predict surfactant retention (Solairaj et al., 2012a). Surfactant retention is very important to the economics of a chemical EOR project because the loss of surfactant in the reservoir (e.g. due to adsorption and trapping) can greatly increase the surfactant quantity required, and therefore the surfactant cost for a project. The correlation predicts the amount of surfactant retention as a mass ratio (i.e. milligrams of surfactant per gram of rock). The parameters used in the correlation included the total acid number (TAN) of the crude oil, temperature, co-solvent concentration, salinity of the polymer drive, mobility ratio, and molecular weight of the surfactant mixture (Solairaj et al., 2012a). The mobility ratio was calculated as the ratio of steady state waterflood pressure drop at residual oil saturation to steady state polymer drive pressure drop at residual oil saturation to chemical adjusted to the same flow rate (Solairaj et al., 2012a). The data used in this correlation was based on dynamic surfactant retention measurements using novel surfactants in both sandstones and carbonates. Overall surfactant retention is similar for sandstone and carbonate, and although adsorption is different between these two rock types, trapping possibly accounts for the similarity in overall retention (Solairaj et al., 2012a).

SUMMARY

This chapter provided a technical foundation for chemical EOR, focusing on theory, mechanisms, and laboratory experimentation, and ultimately showing their usefulness and relevance in the predictive capability of a reservoir-to-market model. The

various types of chemicals used in chemical flooding, as well as their purpose and interactions were described in detail, including: surfactant, co-surfactant, co-solvent, alkali, polymer, and electrolytes. Phase behavior experimentation was described in detail as a quick, inexpensive method for screening well performing chemical formulations. Core flood experiments were described as a method to validate chemical formulations from phase behavior experiments, and provide calibration and/or history match data used in chemical flood simulation. Chemical flood simulation was then identified as a method that could be used to provide well performance input into a reservoir-to-market model.

Several necessary input parameters for a reservoir-to-market model were noted for their sensitivity and significance on economic feasibility because of their relatively high Opex, which included well performance, materials, and source water. Because of their significance, the importance of uniquely describing these inputs in the reservoir-to-market model for the particular field of interest was noted. The chemical formulation design process in the laboratory helps optimize chemical concentrations and use available source water (even extremely hard, saline water), which can vastly improve project economics. Well performance for a reservoir-to-market model can be obtained from simulation output, or well history data from analogue fields, and ultimately determines the expected injection/production rates and general economics associated with fluid streams. However, it is important to describe well performance accurately, given that it determines Opex and Capex level and revenue from produced oil, all of which have a significant effect on project economics.

CHAPTER 4: ECONOMIC ASPECTS OF CHEMICAL EOR PROJECT VALUATION

INTRODUCTION

Economic evaluation is crucial when assessing an oil and gas opportunity because ultimately the final investment decision should be largely based on the expected amount of value realization. Figure 15 shows a general overview of cumulative discounted cash flows for a typical oil/gas project, particularly a chemical flood. Early identification and screening activities typically require relatively little investment or cash outflow. A project that passes the screening phase will undergo a pilot, which can take a decent amount of capital/cash outflow depending on the type, size, and scope of the pilot. A project that passes the pilot phase may undergo additional, larger pilots (not shown in Figure 15), but will ultimately pass a final investment decision (FID) before undergoing full-field development. Full-field development takes a significant amount of investment/cash outflow. Some cash inflow begins to occur during development, but only later in development does cash inflow equals and then exceeds cash outflow (i.e. the minimum point in Figure 15). It is typically not until the operation/production period (i.e. late or post-development) that cumulative discounted cash flow turns positive. Recompletions, infill drilling, or phase development drilling (not shown) can occur during this period as well. The end of the project life is generally when cumulative discounted cash flow no longer increases but decreases, at which point the field is divested or abandoned, and where abandonment costs may be incurred. Because of the large amount of capital investment after FID and the potentially long time period until positive cash flow, front-end engineering/loading studies, such as reservoir-to-market simulation, are important to prove project profitability and enable better informed decision making. This chapter

discusses the basic economic workflow for oil and gas projects, objective function metrics used for project screening, and various economic inputs specific to chemical EOR projects.

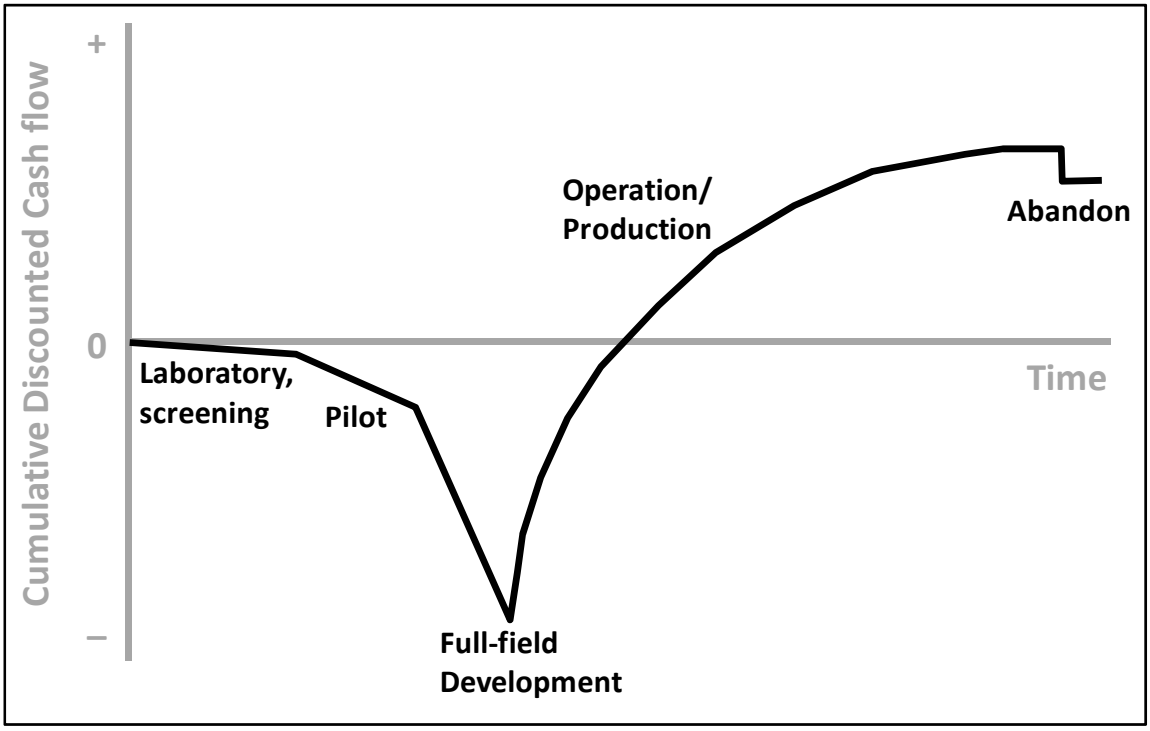

Figure 15: Simplified cumulative discounted cash flow curve over the lifetime of a chemical flood project.

BASIC ECONOMIC WORKFLOW

A basic economic workflow models the various cash inflows (revenue, etc.) and outflows (expenses, taxes, etc.) over a project's life. Ultimately, the cash flow, or net income (or loss), at given points in time or over the project life can be calculated, and provide a metric for the profitability or economic feasibility of a project. This section will

detail the various cash inflows, outflows, and cash flow calculations, and the next section will discuss the various economic metrics.

REVENUE

Revenue is the main type of cash inflow and is generally the amount of hydrocarbon production during a given period of time multiplied by the hydrocarbon unit price. Because both oil and gas can be produced, revenue for each hydrocarbon type must be calculated and summed to get the total revenue. Any gas that is flared must not be considered in the revenue calculation. For most chemical EOR projects in mature fields, oil is the main produced hydrocarbon, and the gas component can be largely ignored for screening purposes. However, the general equation for revenue, R_n, during a given time period, n, is shown below:

$$R_n = Q_{o,n} * P_{o,n} + Q_{g,n} * P_{g,n}$$

where $Q_{o,n}$ and $Q_{g,n}$ are the oil and gas production, and $P_{o,n}$ and $P_{g,n}$ are the oil and gas price during a given time period (n), respectively.

Oil and Gas Price

Oil commodity price is probably the most important determining factor as to whether a chemical EOR project proceeds or not; however, it is also one of the largest sources of uncertainty. Accurately predicting oil price over a project life lasting several decades has historically proven very difficult, although several models and approaches exist in the literature (historical and futures prices shown in Figure 16). Typically for screening, a constant oil price is assumed over the life of the project; however, it is important to at least consider the how oil price can fluctuate and how people have

attempted to model this. Therefore, at the end of this chapter, an oil price model will be created to forecast future oil price, which will be considered in the reservoir-to-market model. The remainder of this subsection will focus on small adjustments in oil price, including price inflation/escalation and/or quality. Other price adjustments, such as transportation, can be accounted for in the oil price, but for this basic screening study, oil price will be considered at the wellhead and/or export pipeline, and only basic price adjustments (e.g. quality correction, price inflation) will be mentioned.

Price inflation/escalation

Oil price at a given time period (n) in the future can be generated by various pricing models. However, the most basic model considers a base oil price at the present time, given by P_o, inflated to a future value at a given time period, $P_{o,n}$, using an inflation rate, $r_{infl,P}$, over one time period. The following equation shows this:

$$P_{o,n} = P_o * \left(1 + r_{infl,P}\right)^n$$

Another way of varying price is with price escalation factors, where a future price at a given time period ($P_{o,n}$) equals the current price (P_o) multiplied by an escalation factor for a given time period, given by $ef_{n,P}$. For the simple inflation price model shown previously, the escalation factor at a particular time would simply be: $ef_{n,P} = \left(1 + r_{infl,P}\right)^n$. Because cash flows are calculated at discrete periods in time (quarterly, annually, etc.), escalation factors can be calculated discretely, and do not necessarily have to follow a continuous equation. However, as mentioned previously, for screening purposes, a constant oil price is usually assumed over the project life.

Quality Corrections

Oil and gas commodity prices are commonly adjusted based on their quality. For oil, quality can vary depending on its API gravity and sulfur content (i.e. sweet or sour crude). Typically, lighter oils having a higher API gravity fetch a higher price than heavier oils with a lower API gravity, and low sulfur (i.e. sweet) crudes are priced higher than high sulfur (i.e. sour) crudes. For gas, price can be adjusted depending on BTU content (with higher BTU gas having a higher value) and impurities such as sulfur or carbon dioxide.

A simple way to perform an API quality correction is by adjusting the oil price a certain amount depending on how its API gravity differs from the API of a base oil. For example, say West Texas Intermediate (WTI) is the base oil, with an API gravity around 40. An oil of interest with an API of 35 will have a quality correction applied to the 5 API units of difference. The API difference will be multiplied by a quality correction, in terms of price per API per volume (e.g. $/API/STB), to obtain an API quality correction as a price per volume, which will ultimately be applied as a correction to the price of the base oil. The equation for the API quality correction, API_{qc}, given in units of $/STB, is:

$$API_{qc} = (API_{oil} - API_{base\ oil}) * k_{API,qc}$$

where API_{oil} and $API_{base\ oil}$ are the API values of the oil of interest and base oil (e.g. WTI), respectively, given in API units, and $k_{API,qc}$ is the API quality correction term given in units of $/API/STB.

A sulfur quality correction can also be applied to the oil price depending on the percentage of sulfur present in a particular crude oil. For example, say 0.5% sulfur content is a standard allowable limit, and a fixed price per volume correction is applied

for every 0.1% incremental increase in sulfur content above the 0.5% allowable threshold. A general equation for calculating the sulfur quality correction, c_{qc}, given in units of $/STB, is:

$$c_{qc} = \left(c_s - c_{s,limit}\right) * k_{s,qc}$$

where c_s and $c_{s,limit}$ are the sulfur contents of the oil of interest and upper allowable limit, respectively, given as a percentage (%), and $k_{s,qc}$ is the sulfur content quality correction term given in units of $/%/STB.

ROYALTIES AND FEES

Royalty and severance ad valorem taxes generally occur as a percent of revenue (in cash) or production (in kind), and are taken out of the revenue or produced volume. Royalties and severance ad valorem taxes are part of the more general payments to the government (i.e. host government take) that also includes other taxes and production bonuses among other things. The basic equations for calculating the royalty tax, $T_{royalty,n}$, and severance ad valorem tax, $T_{sev\ ad\ val,n}$, at a given time period (n), both given in dollar ($) units, are as follows:

$$T_{royalty,n} = r_{royalty} * R_n$$
$$T_{sev\ ad\ val,n} = r_{sev\ ad\ val} * R_n$$

where $r_{royalty}$ and $r_{sev\ ad\ val}$ are the royalty and severance ad valorem tax rates in percentage (%) units, respectively, and R_n is revenue given in dollar units ($). These taxes can be collectively termed non-income taxes to differentiate them from ordinary

income taxes taken as a percentage of pre-tax income (to be explained in a later section). Therefore, these non-income taxes, $T_{non-income,n}$, for a given time period (n) can be collectively summed as:

$$T_{non-income,n} = T_{royalty,n} + T_{sev\ ad\ val,n}$$

EXPENDITURES

The two basic types of expenditures for a project include operating expenses (Opex) and capital expenses (Capex). Technical costs are also a more general term for both Opex and Capex. Opex can be thought of as activity-based costs, where a good or service is purchased and consumed within the particular time period the expense is incurred. However, for simplicity, Opex is categorized into two types: fixed and variable costs. Fixed costs occur whether a project is in operation or not, and are usually a percentage of the cumulative Capex (where the percentage depends on the item). Variable costs are usually a cost per increment of production (i.e. $/STB) and vary depending on the quantity of production during a given time period. The general equation for total Opex, $E_{tot,n}$, given in dollars ($), for a given time period, n, is the following:

$$E_{tot,n} = E_{fix,n} + E_{var,n}$$

where $E_{fix,n}$ and $E_{var,n}$ are the fixed and variable Opex (in dollars), respectively, for a given time period (n). The fixed and variable Opex shown are the summations of all individual fixed or variable Opex incurred in a given time period, and also that individual

fixed Opex are percentages of particular individual Capex. Therefore, the variables can be subdivided further as such:

$$E_{fix,n} = \sum_{i=1}^{m} r_{C,i} * C_{n,i}$$

where $C_{n,i}$ and $r_{C,i}$ are the individual (i) Capex item (for a given time period) and percentage multiplier of that Capex item, respectively, of the total items (m). Similarly:

$$E_{var,n} = \sum_{i=1}^{m} E_{var,n,i}$$

where $E_{var,n,i}$ is the individual (i) variable Opex item of the total number of variable Opex items (m) for a given time period (n). The overall Opex equation for a given time period (n) can now be expanded as such:

$$E_{tot,n} = \sum_{i=1}^{m} \left(r_{C,i} * C_{n,i} + E_{var,n,i}\right)$$

Capex consists of expenditures for an asset having a usage lifespan beyond a taxation period. Capex typically are large expenditures for wells, facilities, and/or equipment at the start of a project, but can also consist of equipment/facility upgrades as well. Because the lifespan of a Capex lasts longer than a taxable period, the entire expenditure usually cannot be deducted from revenue at the time of purchase, but is generally allocated in portions over the expected lifetime of the asset. This type of cost allocation is referred to as depreciation, which is intended to represent the gradual value

loss of capital assets. Therefore, $C_{n,i}$ in the equations above essentially represents the depreciable Capex of an individual (i) Capex item for a particular time period (n), assuming the item can still be depreciated at that time period.

Depreciation

Depreciation can relate to either the decrease in value of an asset or the cost allocation of an asset over its time period of use. The latter is of most relevance to calculating net income and other metrics of project profitability. Oil and gas projects typically involve equipment, facilities, and installations that are large capital expenditures, have an expected lifespan more than a year, and lose value from year-to-year. Because expenditures are subtracted from revenue prior to calculating income taxes, various depreciation methods allow for a systematic way of accounting for large capital expenditures over a given period of time.

Capital expenses can contain either or both tangible and/or intangible portions. Tangible assets are literally anything that can be touched, such as a facility, equipment, or a scheduled job (involving acquisition/construction of a depreciable asset), while intangible assets describe something that can have ownership but cannot be touched (e.g. exploration rights, purchase options, etc.). The simplest way to describe an asset having both tangible and intangible portions is to designate percentages of the total capital expense as the percent tangible and/or intangible. Intangible assets or parts of assets are commonly depreciated completely in the given expense period. For tangible assets (or portions of assets), the asset life and salvage value (a residual value which cannot be depreciated) are defined, as well as the start of depreciation. Three common options for starting depreciation are as built (well drilling begins, job starts, etc.), in service (first production day or job start date), and when completes (construction, drilling, and/or job

ends, etc.). With these basic inputs considered, several methods exist for calculating the cost allocations of the depreciating asset over time:

- **Percentage:** Allocates a specified percentage of the remaining capital expense, which is a decreasing amount every period. Expected asset life is largely irrelevant.
- **Straight line:** A capital expense is allocated equally every period, which is simply calculated as the total capital expense divided by the asset life (i.e. number of periods).
- **Expensed:** Allocated capital expense to the period corresponding to the start of depreciation.
- **Units of production:** Asset life is measured in units of production rather than time period, and the allocated expense is calculated using a period production / lifetime production factor. This type of depreciation can pertain to wells and other facilities.

Several other depreciation methods exist (declining balance, sum years digit, MACRS, etc.), but are not discussed here.

The simple economic modeling used in this study will use a basic, straight line depreciation method. For a particular Capex item (i) having an initial, total Capex, C_i, the depreciable Capex, $C_{n,i}$, for a given time period (n) is given as:

$$C_{n,i} = \frac{C_i - S_{t_i,i}}{t_i}$$

where t_i is the total depreciable lifespan of the given Capex item (i), represented as the total number of individual depreciable time periods, and $S_{t_i,i}$ is the salvage value of the

item at the end of its depreciable lifespan. The total depreciable Capex, C_n, of all items at a given time period (n) will then be given as:

$$C_n = \sum_{i=1}^{m} C_{n,i} = \sum_{i=1}^{m} \frac{C_i - S_{t_i,i}}{t_i}$$

Items that have already undergone their full depreciation will not be part of the depreciable Capex at a given time period (n).

Capital escalation

Capital escalation is a method of adjusting expenditures during the life of a project to reflect price changes caused by a variety of factors (inflation, demand increase, etc.). The most basic way of adjusting costs (e.g. new Capex and/or variable Opex) is by using an inflation rate, $r_{infl,C}$, in a basic cost escalation factor, $ef_{n,C} = \left(1 + r_{infl,C}\right)^n$, to serve as a cost multiplyer for a given time period (n).

PRE-TAX INCOME

Pre-tax income is the earnings during a certain time period after expenses, royalties, and other fiscal costs have been deducted, but prior to income taxes being deducted. Fiscal costs are generally defined as the sum of royalties and other government payments (excluding ordinary income tax), Opex, and depreciated Capex. Given the equations described in previous sections, the fiscal costs for a given time period, FC_n, are:

$$FC_n = T_{non-income,n} + E_{tot,n} + C_n$$

Pre-tax income, $I_{pre-tax,n}$, for the same given time period can them be calculated as:

$$I_{pre-tax,n} = R_n - FC_n$$

INCOME TAX

Income tax is deducted from the pre-tax income, and, in the United States, commonly consists of state tax and federal tax percentages. Calculating income tax, $T_{income,n}$, for a given time period (n) is relatively straightforward:

$$T_{income,n} = \sum_{j=1} r_{income,j} * I_{pre-tax,n}$$

where $r_{income,j,n}$ is a particular income tax, j, which can, for instance, be state income tax, federal income tax, etc.

NET INCOME

Net Income is essentially the cash flow after taxes have been taken out. A positive net income is referred to as profit, while a negative net income is a loss. Net income forms the basic building block for a number of different economic objective functions to serve as profitability metrics, which will be discussed in the next section. The equation for net income, $I_{net,n}$, for a given time period (n) is as follows:

$$I_{net,n} = I_{pre-tax,n} - T_{income,n}$$

OBJECTIVE FUNCTION METRICS FOR PROJECT SCREENING

An objective function is a quantitative criterion used to assess and/or screen a particular project. Sanz and Miller (1994) discusses several different types, including the internal rate of return (IRR), net present value (NPV), payback period, and profit to investment ratio (RPI), which is also the value to investment ratio (VIR). Each metric can serve a different purpose in assessing projects. NPV tends to be the best metric for assessing total expected returns from a project. IRR is essentially an effective rate of return expected from a project, and complements NPV in being the discount rate at which NPV equals zero. Payback period is a simple metric for determining the period of time required for returns to fully repay the original investment cost. Other metrics such as VIR and unit technical cost (UTC) are useful when capital or production constraints, respectively, are present in a project.

NET PRESENT VALUE

Net present value of a given project is the sum of the present values (PVs) of net cash flows expected at future points in time. Future cash flows are discounted back to the present time using a discount rate, which accounts for the time value of money, or the concept that money available now is worth more than money in the future because it could be earning interest. The discount rate is also known as the cost of capital, which commonly consists of two types: debt and equity cost of capital. Debt cost of capital is equal to the after tax interest payment to lenders. Equity cost of capital is the opportunity cost, or what investors could be getting (appreciation plus dividends) if they invested in a similar risk portfolio. Total cost of capital is the weighted sum of debt and equity cost of capital, which comprises the discount rate. The general equation for NPV, when

discounting all future cash flows from each time period, n, of all the time periods during the project life, N, by a discount rate, $r_{discount}$, is as follows:

$$NPV = \sum_{n=1}^{N} \frac{I_{net,n}}{(1 + r_{discount})^{t_n}}$$

where t_n is the elapsed time period from the present time until time period n.

Another economic metric used to equate profitability and efficiency is the earnings before interest, taxes, and amortization, or EBITA. Some companies have significant fixed assets and/or intangible assets subject to large amortization or depreciation charges, which can skew earnings. Also, some companies have a large amount of debt that deducts a significant amount from earnings in the form of interest. Therefore, EBITA is a reasonable earnings metric to compare companies across different sectors.

INTERNAL RATE OF RETURN

The internal rate of return, or IRR, for a particular project is defined as a certain discount rate that makes the NPV of all future cash flows equal to zero. In essence, IRR can be thought of as an effective interest rate that a project will provide if it is implemented. IRR is solved for using the NPV equation and substituting in IRR for the discount rate, and zero for the NPV:

$$0 = \sum_{n=1}^{N} \frac{I_{net,n}}{(1 + IRR)^{t_n}}$$

VALUE TO INVESTMENT RATIO

The value investment ratio, or VIR, of a particular project is the ratio of present value of all future cash flows (NPV) to the present value of initial capital expenditures. This ratio helps quantify the amount of value created by a particular amount of investment. It is important to rank projects according to this metric when capital constrained, because it allows the project to be selected that will generate the largest value for a given amount of capital. However, when not capital constrained, NPV is a better metric at determining total project value. The equation for VIR is expressed as follows:

$$VIR = \frac{NPV}{\sum_{i=1}^{m} C_i}$$

where $\sum_{i=1}^{m} C_i$ is the summation of the initial, present values of each of m individual Capex items (i) having initial, total Capex values of C_i.

UNIT TECHNICAL COST

Unit technical cost, or UTC, essentially defines a cost per produced volume of hydrocarbon. Although projects are generally selected based on the highest NPV or VIR (if capital is constrained), UTC can be applicable when a production ceiling constrains the maximization of NPV. The equation for UTC is as follows:

$$UTC = \frac{PV_{Capex} + PV_{Opex}}{PV_{Production}} = \frac{\sum_{i=1}^{m} C_i + \sum_{n=1}^{N} \frac{E_{tot,n}}{(1 + r_{discount})^{t_n}}}{\sum_{n=1}^{N} \frac{Q_{o,n}}{(1 + r_{discount})^{t_n}}}$$

Only oil production is included in the equation. If gas is also present, it would be included as equivalent barrels to have a single UTC value collectively for oil and gas.

PAYBACK PERIOD

Payback period is simply the period of time required for returns to fully repay the original investment cost.

OIL PRICE MODELING

Oil price modeling attempts to forecast dynamic changes in oil price over the life of a project. Oil price has historically had high volatility, occasional price jumps beyond typical fluctuations, nearly normal distribution of percent annual changes, and a tendency to revert to a long term mean (Begg and Smit, 2007). Models that account for one or more of these factors helps capture some uncertainty associated with oil price, which can enable more informed decision making.

COMMON OIL PRICE MODELS

Begg and Smit (2007) describe and compare four different price models: simple probabilistic, Geometric Brownian Motion (GBM), mean-reversion (MR), and MR with jumps (i.e. jump diffusion). In this section, only GBM and MR will be discussed in detail, and MR will ultimately be used for oil price modeling in the chemical EOR reservoir-to-market model. The simple probabilistic model, though quite elementary, is easy-to-use as it simply adds some variability to a flat real price. GBM is the 'random walk' where prices randomly vary based on pre-defined volatility and current price. MR builds upon GBM by including an average price at which the 'random walk' can revert back to. MR with jumps, or jump diffusion, builds upon MR by including a jump, or price spike, effect. MR with jumps is more relevant in electricity price modeling, where prices have historically increased nearly three orders of magnitude within about a month. Although

supply shocks can spike oil pricing, storability of oil generally minimizes this type of extreme shock, though price jumps can occur beyond typical fluctuations. For this study, the volatility embedded in the GBM and MR models is assumed to reasonably characterize price changes.

Geometric Brownian Motion (GBM)

GBM, or also known as 'random walk,' characterizes the movement (i.e. zigzagging) of something, say oil price, from a current position according to two different effects: non-random drift and random volatility (Blanco et al. 2001). The GBM process assumes price changes are independent of each other, and have a constant mean and volatility. For oil price, returns generally have a lognormal distribution, which restricts the price from falling below zero.

Begg and Smit (2007) give the differential equation describing GBM for a price,P, at a particular time, t, as such:

$$\frac{dP}{P} = \alpha dt + \sigma\varepsilon\sqrt{dt}$$

where α is the percentage drift, σ is the percentage volatility, and ε is a standard normal random variable. The equation sums together the non-random drift effect (αdt) and the random volatility effect $\left(\sigma\varepsilon\sqrt{dt}\right)$.

Begg and Smit (2007) as well as Blanco et al. (2001) show the analytical solution of the GBM written in a numerical format as such:

$$P_{n+1} = P_n e^{\left[(\alpha - 0.5\sigma^2)(t_{n+1} - t_n) + \sigma\varepsilon_{n+1}\sqrt{t_{n+1} - t_n}\right]}$$

or logarithmically as such:

$$ln(P_{n+1}) = ln(P_n) + (\alpha - 0.5\sigma^2)(t_{n+1} - t_n) + \sigma\varepsilon_{n+1}\sqrt{t_{n+1} - t_n}$$

where $(n+1)$ and (n) correspond to discrete time steps. As described previously, $P_n e^{(\alpha - 0.5\sigma^2)}(t_{n+1} - t_n)$ represents drift effects, while $\sigma\varepsilon_{n+1}P_n\sqrt{t_{n+1} - t_n}$ represents volatility effects.

Blanco et al. (2001) describe several shortcomings of the GBM model, such as oil prices not exactly being lognormally distributed, lognormal distribution underestimating extreme price changes, unknown and/or non-constant volatilities, and large volatilities unrealistically dominating drift effects.

Mean-reversion (MR)

MR does not assume price changes are independent, which was a potential shortfall of GRM (Begg and Smit, 2007), but rather that prices have a tendency to gravitate towards a normal equilibrium price level governed by production cost and demand (Blanco and Soronow, 2001a). For example, the market reality for a plunge in oil price is for producers to decrease supply, which would lead to a price rebound.

The drift term in the MR model is governed by the difference between current and mean reversion prices, and the mean reversion rate. Begg and Smit (2007) also give the differential equation describing MR for a price,P, at a particular time, t, as such:

$$\frac{dP}{P} = \eta(P - P^*)dt + \sigma\varepsilon\sqrt{dt}$$

where η is the mean reversion rate, P^* is the mean reversion price, σ is the percentage volatility, and ε is a standard normal random variable. The first part of the equation $\eta(P - P^*)dt$ is referred to as the mean reversion effect, or expected trend, as opposed to the drift effect in the GBM.

Begg and Smit (2007) as well as Blanco et al. (2001) show the solution of the MR written in a numerical format as such:

$$P_{n+1} = e^{\left[\left[ln(P_n)e^{-\eta(t_{n+1}-t_n)}\right]+\left[\left(lnP^*-\frac{\sigma^2}{4\eta}\right)\left(1-e^{-\eta(t_{n+1}-t_n)}\right)\right]+\sigma\varepsilon\sqrt{\frac{1-e^{-2\eta(t_{n+1}-t_n)}}{2\eta}}\right]}$$

Begg and Smit (2007) describe that the desired long term mean reversion price P^* is related to the long term mean derived from historical data, P', by the following:

$$P^* = P'e^{\sigma^2/4\eta}$$

The mean reversion rate tends to differ for each commodity, for example oil markets experience months or years before prices revert to a mean, natural gas markets are somewhat faster, and electricity markets have sudden price spikes with very rapid mean reversion (Blanco and Soronow, 2001a).

GENERATING AN OIL PRICE MODEL

Several model input parameters are required depending on the type of oil price model used.

Estimating GBM parameters – volatility and drift

There are several methods for estimating expected volatility, for example, historical prices could be used or option market prices (Blanco et al., 2001). Blanco et al. (2001) detail a simple method for calculating volatility from historical data:

1. Obtain historical oil spot price data (e.g. daily, weekly, or monthly) over a period of time (e.g. 10 years).
2. Calculate logarithmic price changes between prices of adjacent time periods:$ln(P_n) - ln(P_{n-1})$
3. Calculate the standard deviation (i.e. volatility) of the logarithmic price changes
4. Use the 'square-root-of-time' rule to annualize volatility (for instance, 1% weekly volatility is 1% * sqrt(52) = 7.2% annualized volatility)

The models discussed assume constant volatility; however, to capture more variation, volatility can be defined by a distribution and modeled probabilistically.

Estimating MR parameters – mean reversion price and rate, and volatility

Current forward/futures prices are the market's unbiased estimate for future spot prices that can be used as time dependent mean reversion price levels (Blanco and Soronow, 2001a). Blanco and Soronow (2001a) detail a procedure for calculating mean reversion rates, mean reversion levels, and volatilities. The first four steps are identical to those used for estimating volatility, and subsequent steps are as such:

1. Calculate absolute price changes between prices of adjacent time periods: $P_n - P_{n-1}$
2. Plot absolute price changes (y-axis) versus previous price levels (x-axis) (i.e. $P_n - P_{n-1}$ versus P_{n-1}); find the slope, y-intercept, and residual standard deviation of a linear regression

3. Calculate the mean reversion level, which is equal to the y-intercept divided by the negative slope; calculate the mean reversion rate, which is the negative slope
4. Calculate volatility as the residual standard deviation divided by the mean reversion rate; note that calculating volatility using this method generally results in a lower value than using the method described previously

Historical data and model parameters

The methods provided by Blanco et al. (2001) and Blanco and Soronow (2001a) were followed to construct a MR oil price model and generate oil price forecasts. Daily spot prices for Brent crude oil (e.g. from the New York Mercantile Exchange – NYMEX) were obtained over the past 10 years. Additionally, monthly futures prices for the next 5 years were also obtained. Figure 16 plots the historical and futures price data for Brent crude oil.

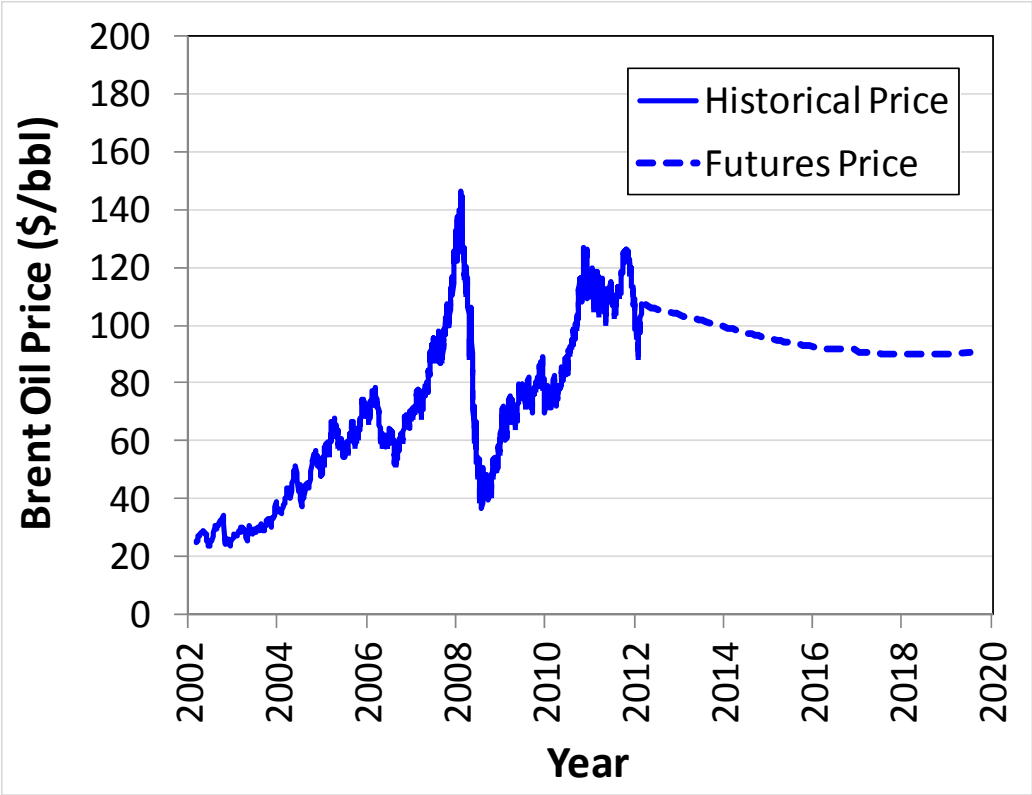

Figure 16: Historical daily spot prices for the past 10 years and monthly futures prices for the next 5 years for Brent crude oil.

From the historical price data, logarithmic price changes between adjacent monthly prices were calculated over only the past 5 years, and the standard deviation, or volatility, of these changes was calculated. The monthly standard deviation was found to be 12.14%. To annualize this volatility, the 'square root of time' rule was applied, and the annualized volatility was calculated to be 42.04%. With these parameters, a GBM model could be constructed; however, additional parameters were calculated in order to construct a MR model. From the futures price data, logarithmic price changes between adjacent monthly prices were calculated for 5 years in the future, and the standard deviation, or volatility, of these changes was calculated. Absolute price changes were

plotted versus previous price levels, and a linear regression curve was fitted. The slope, y-intercept, and residual standard deviation were found to be -0.0181, 1.4923, and 0.1106, respectively. The mean reversion rate was then calculated as the negative slope, which was 0.0181. The mean reversion level was calculated from the slope and y-intercept, and found to be 82.50. Volatility was calculated from the residual standard deviation and mean reversion rate, and found to be 0.13%. Therefore, the mean reversion price and volatility used in the MR model were 82.50 and 0.13%.

Model generation

The mean reversion oil price model was used to forecast prices 15 years into the future. Figure 17 and Figure 18 show ten and one-hundred, respectively, generated oil price forecasts that are overlain on historical and Brent crude oil prices. The price fluctuations seem reasonable, given the price history. For example, the price history shows crude oil fluctuating by a factor of 6 from 2003 to 2013. Individual price forecasts will fluctuate by a little more than 2-fold, and, when considering all price forecasts, fluctuations are from $50/STB to $250/STB (a factor of 5).

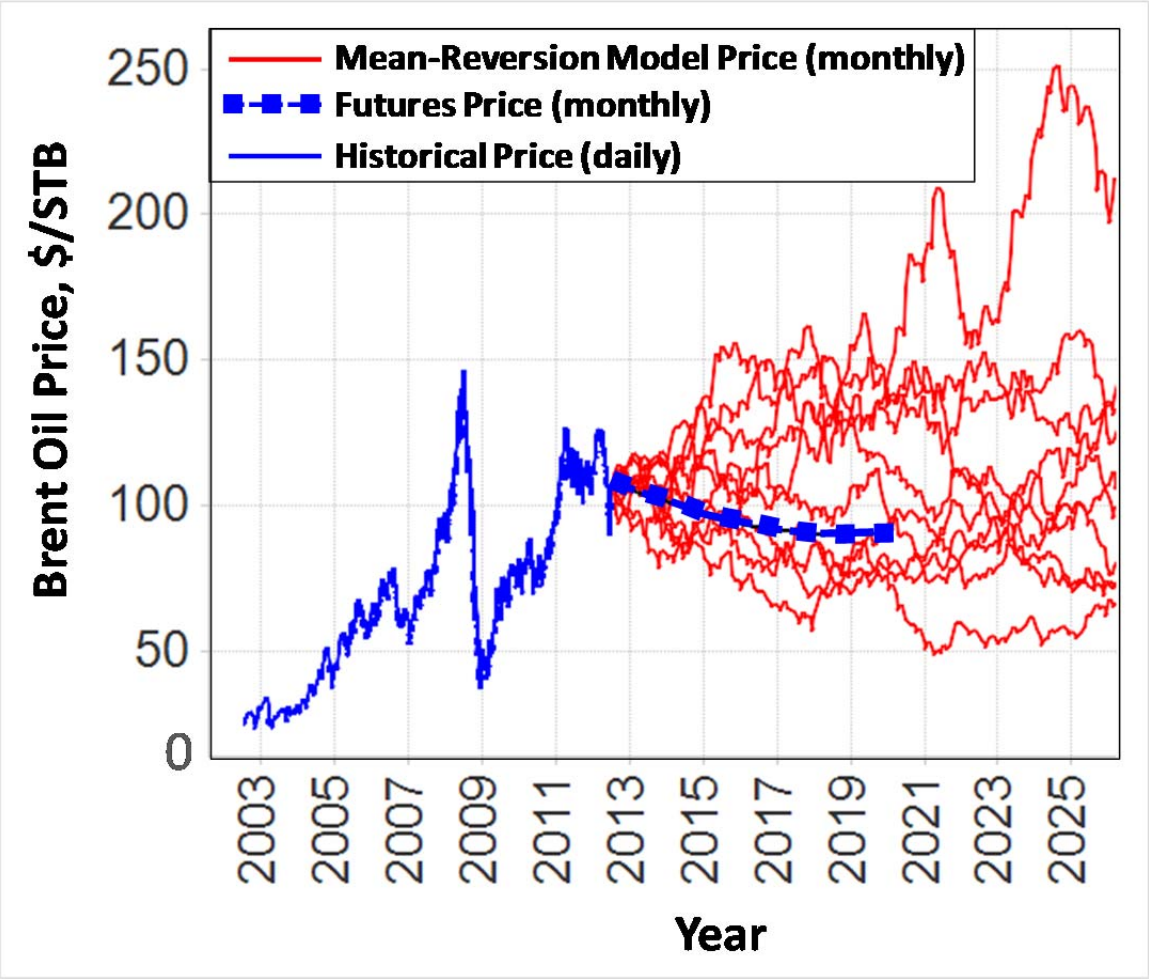

Figure 17: Ten mean reversion oil price model forecasts overlain on historical and futures Brent crude oil prices.

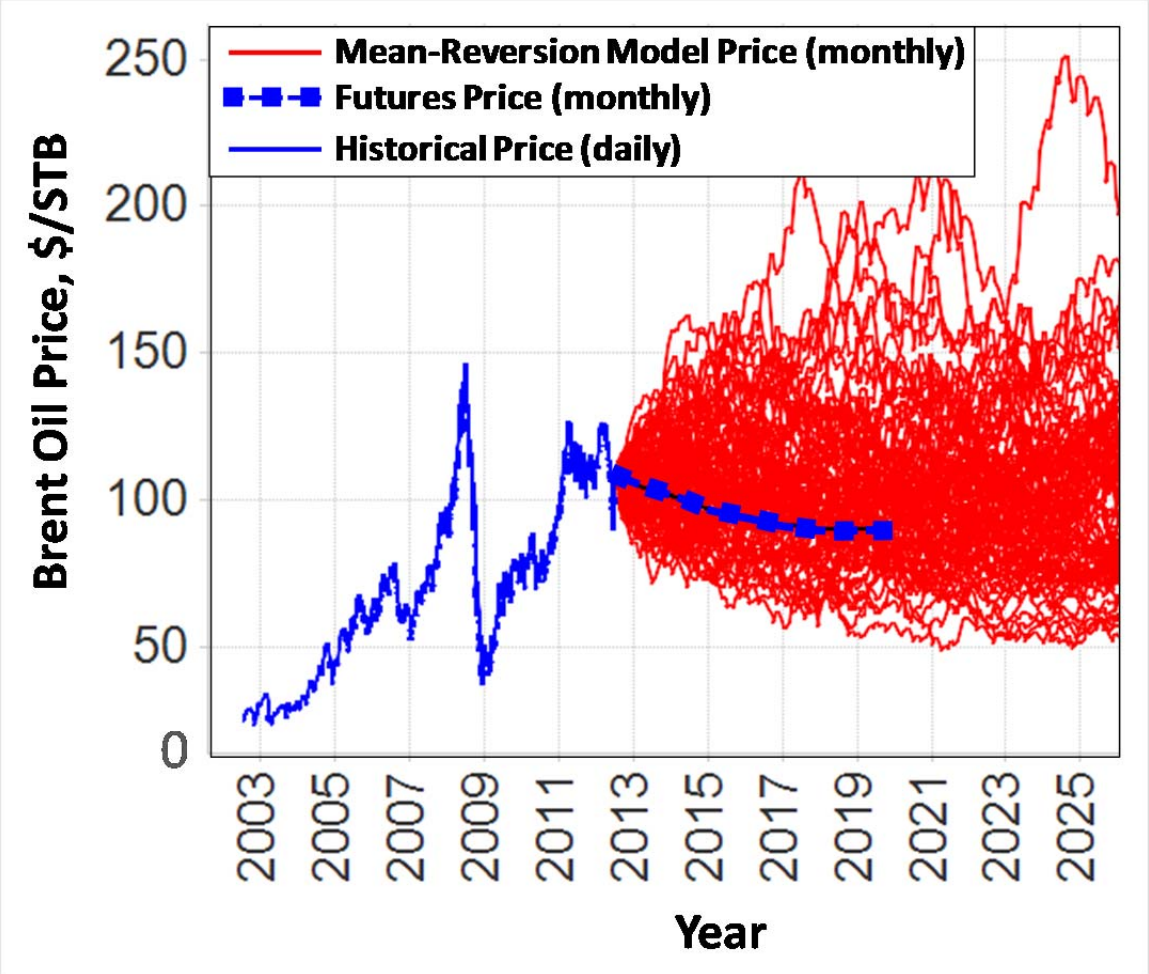

Figure 18: One hundred mean reversion oil price model forecasts overlain on historical and futures Brent crude oil prices.

SUMMARY

This chapter provided an economic workflow for modeling the various cash inflows (revenue, etc.) and outflows (expenses, taxes, etc.) over a project's life. A general overview of cumulative discounted cash flow for a typical oil/gas project was discussed as a method of understanding project economics throughout the life of a project. Various

stages during the project life that impact cash flow include: early identification and screening, piloting, final investment decision and development, production and operation, and abandonment. Several economic metrics were discussed that can assess the profitability or economic feasibility of a project, which include NPV, IRR, VIR, UTC, and payback period. A mean reversion oil price model was constructed to forecast future oil prices.

CHAPTER 5: DEFINING A RESERVOIR-TO-MARKET WORKFLOW FOR CHEMICAL EOR USING PROJECT DEVELOPMENT STRATEGY, DE-RISKING, SURFACE/SUBSURFACE CONCEPTS, AND CASE STUDIES

INTRODUCTION

Building a reservoir-to-market model for determining the feasibility of a chemical EOR project requires some understanding of the overall project development strategy. Because of the technical and economic uncertainty and risks associated with a chemical EOR project, Du et al. (2011) outlines a staged development concept consisting of several key stages: laboratory testing (chemical testing, core flooding, etc.), piloting (single well, pattern, etc.), and full-field development (phased or un-phased). Staged development allows for assessing feasibility during a particular stage, as well as de-risking and optimization for subsequent stages. From a technical perspective, chemical flood simulators are commonly used to model and/or predict core flood, pilot, and full-field performance and feasibility. A reservoir-to-market model can be built early in the project lifecycle to also serve as a tool for assessing feasibility, but more from a combined economic, technical, and logistical perspective. Portions of the reservoir-to-market model can be de-risked, updated, and/or optimized as data is gathered throughout the various stages, and the model as a whole can aid in decision-making as well. This chapter describes the development strategy stages, piloting and full-field surface and subsurface concepts and engineering, various risks/uncertainties, de-risking and feasibility assessment, and relevant offshore/onshore case studies to help understand the components and workflow for a reservoir-to-market model.

DEVELOPMENT STRATEGY

When a potential chemical EOR opportunity has been screened for study and potential implementation, a staged development process is important for de-risking uncertainties (Du et al., 2011). Du et al. (2011) discuss several key stages for project development, which include: laboratory testing, piloting, and full-field development. Each of these stages contains several sub-stages important for de-risking, which are explained further in the following sub-sections.

- **Laboratory testing:** Laboratory testing was discussed in detail in Chapter 3. Typically after a field has been screened as a potential chemical EOR candidate, chemical formulations are screened through various laboratory experiments (phase behavior, aqueous stability, rheology, etc.) on how they perform with the crude oil and formation and/or injection brine from the reservoir/field of interest. Chemical formulation performance is validated using core floods for a variety of feasibility and de-risking factors. Laboratory testing and core flooding help calibrate models in a chemical flood simulator to optimize pilot and full-field development designs.
- **Piloting:** Pilot projects are a crucial intermediate de-risking step between laboratory study and full-field implementation. They are essentially field experiments used to prove technical feasibility of the laboratory findings in the field, and to better define and optimize the full-field development. Several types of pilots exist (single well, pattern pilot, etc.) and one or more can be selected to prove feasibility with respect to injectivity, de-saturation, and/or recovery among other things.

- **Full field development:** Full field development and deployment occurs after the final investment decision (FID) has been made. It consists of the delivery of all the wells, materials, and facilities, as well as implementing the injection schedule and reservoir surveillance strategy. However, although post-FID may seem like a point-of-no-return, there is still opportunity for de-risking and optimization. For example, a phased approach can be used to develop, say, one part of the field first, then apply learnings to other parts of the field (phase 2, 3, etc.) later.

Staged development can be thought of as a staircase, where 'stepping up' means proving feasibility and advancing to the next stage (Du et al., 2011). Each subsequent stage generally involves larger project costs and a longer time commitment as well. A reservoir-to-market model can be used for the duration of the entire project; however, employing it at earlier stages involves making assumptions about later stage development concepts. These assumptions have uncertainty and risk associated with them that will be de-risked when stepping from stage to stage. The following sections of this chapter though will provide concepts and case studies to serves as analogues for building a reservoir-to-market model.

PILOT TYPES AND OBJECTIVES

Pilot projects can provide information of significant value for a chemical EOR project; however, it is important to define the objectives of a pilot, and aim to accomplish those objectives in as short a time as possible. Pilots will contain either a single well or multiple wells, with each scenario having different advantages and objectives. The length of time and cost of a single well pilot compared to a producing multi-well pilot typically differs by an order of magnitude. Depending on whether the project is onshore or

offshore, a single well pilot can last one to a few months and cost several hundred thousand to a couple million dollars, while a multi-well pilot lasts one to a few years and costs a few million to tens of millions of dollars. For de-risking purposes, chemical EOR projects will typically run a single-well pilot first, assess feasibility (e.g. de-saturation, injectivity), then run a multi-well pilot before making the final investment decision for commerciality.

KEY RISKS AND DE-RISKING

Chai et al. (2011) discusses key risks of chemical EOR projects that are important to assess/de-risk with pilot projects, and how or if single- and multi-well pilots address these risks. The key risks are summarized as follows:

- Chemical formulation effectiveness (downhole and/or in situ)
- Produced fluids sale-ability (oil and/or gas) and/or disposal (water and/or gas)
- Sweep efficiency
- Injectivity (near- and long-term)
- Scaling (near wellbore, tubing, and pipelines)
- Chemical supply and handling logistics

It is important to assess/de-risk all of these risk categories prior to FID. A single well pilot will not assess all these risks, whereas a longer, more expensive multi-well pilot is able to. However, if a single well pilot proves to not sufficiently de-risk a risk category, the project can be discontinued and the more significant cost of a failed multi-well pilot can be avoided. Chai et al. (2011) describes if and how three different types of pilots can de-risk all of the risk categories: single well Huff-and-Puff pilot, multi-well

observation pilot, and the multi-well producing pilot. The following sub-sections will detail different single and multi-well pilots, and how they can be used for de-risking.

SINGLE WELL PILOTS

A single well pilot can be described by several different names, such as single well chemical tracer (SWCT) test, Huff-and-Puff, or injectivity test among others (Chai et al., 2011; Dijk et al., 2010). This section describes the SWCT test concept and design, the de-risking a SWCT test can and cannot provide, and several different onshore and offshore SWCT test case studies.

Single well chemical tracer (SWCT) test concept

A SWCT test uses chemical tracers to measure the immobile, or remaining, oil saturation usually within several meters radius from the wellbore. It is useful when designing a chemical EOR project to understand how effectively the surfactant slug can de-saturate the reservoir rock, or mobilize oil that was previously immobile without surfactant. Dijk et al. (2010) describes the well-understood SWCT test technology for measuring remaining oil saturation following water flood (Tomich et al., 1973). A partitioning tracer is used that both forms a hydrolyzed product in situ, and has different partitioning characteristics with the oil phase than its hydrolyzed product does. When a tracer is injected in the reservoir and hydrolyzes in situ, differing partitioning characteristics cause different concentration profiles of the two chemicals when the well is flowed back, which ultimately allows remaining oil saturation to be calculated. Ethyl-acetate (EtAc) is a common tracer, which hydrolyzes to ethanol (EtOH) in situ. In a typical SWCT test, EtAc is first injected in a brine-based slug, and itself partially partitions into the oil phase. The well is shut in for a period of time, during which EtAc hydrolyzes to EtOH, which is poorly soluble in oil. The injection fluid is then flowed

back, and concentration profiles are measured versus flowback volume for each chemical. Figure 19 shows idealized SWCT test response curves for tracer (EtAc) and hydrolyzed product (EtOH), and remaining oil saturation can be calculated from the time separation between the two maxima of the curves. Curves from an actual field test will show deviations from non-ideality caused by a number of different factors such as poor well integrity or wellbore cross flow and fluid drift among others (Stoll et al., 2010; Oyemade et al., 2010).

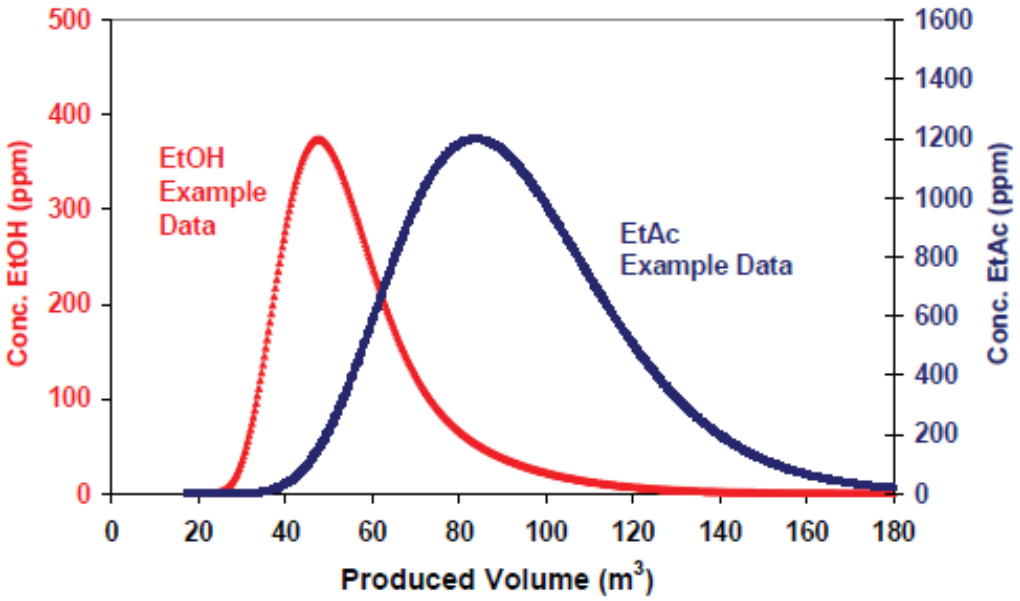

Figure 19: Example idealized SWCT test response curves of tracer (EtAc) and hydrolyzed product (EtOH), as shown in Dijk et al. (2010)

De-risking

Of the risk categories mentioned previously, a single well pilot only assesses a few of them (Chai et al., 2011). Injecting the relatively small chemical slug and fluid volumes helps assess an 'initial injectivity' over a few days or weeks, but does not assess

the longer term injection conformance that injecting more than a pore volume can in a multi-well producing pilot. The chemical formulation effectiveness at oil de-saturation can be assessed near the wellbore (i.e. investigation radius), which is usually very limited in area relative to the commercial scale. Chemical supply and handling logistics are assessed on a small scale of a few batches, rather than continuous supply, mixing, and injection workflow that a producing pilot would require. Oil sale-ability through emulsion breaking and treating cannot accurately be assessed on a production scale using typical surface processing facilities because of the small volumes; therefore more limited information must be gathered through laboratory testing. Scaling is usually not assessed do to the limited timeframe, and sweep efficiency cannot be determined. Despite the limited information single well pilots provide, some useful assessments (e.g. injectivity, chemical formulation effectiveness) can enable decision-making of moving onto a multi-well pilot, conducting further laboratory testing and/or another single well pilot, or project termination. However, making the FID for a commercial-scale project generally does not occur with merely a successful single well pilot and without a multi-well pilot.

Case studies

Salym Petroleum Development (SPD) – Onshore West Siberia

Djik et al. (2010) details the chemical EOR ASP flooding project at the onshore West Salym field in West Siberia. The project workflow started with chemical formulation design using laboratory phase behavior experiments, core flood validation of formula performance, SWCT test pilot, a small-scale multi-well pilot test, and a larger-scale multi-well pilot test.

The chemical formulation that performed well contained a surfactant, co-surfactant, co-solvent, and alkali mixture of two internal olefin sulfonates (branched 24-

28 carbon chain (IOS_{24-28}) surfactant and branched 15-18 carbon chain (IOS_{15-18}) co-surfactant), sec-butyl alcohol (SBA), and sodium carbonate (Na_2CO_3). Phase behavior experiments showed an optimal salinity of 1.3% KCl + 1% Na_2CO_3, which was used for the core flood, SWCT test, and multi-well pilot test. The target optimal salinity was about 2.5% NaCl equivalent, which is slightly lower than the water flood brine currently used for flooding. Hydrolyzed poly-acrylamide (HPAM) polymer Flopaam 3230S (SNF) was used for mobility control, with 1500 ppm providing sufficient viscosity of 2.8 cp (relative to the 2 cp viscosity oil), although 3000 ppm and 5000 ppm could have provided much higher viscosity around 5.5 cp and 13 cp, respectively (Dijk et al., 2010).

A 2 cm diameter and 5 cm length Berea sandstone core with 360 md permeability was prepared, having a 40% remaining oil saturation after water flood (which was 15% above residual). An ASP slug was injected followed by a polymer drive, although the volumes of each were not specified in the study. Oil breakthrough occurred after 0.3 PV, and 70% of remaining oil was recovered as a clean oil bank (with 45-55% oil cut) until surfactant breakthrough occurred at 0.8 PV (although emulsion production started around 1 PV). Surfactant production peaked at around 1.5 PV, and total oil recovery after 2 PV was around 94% (Dijk et al., 2010).

A SWCT test was performed in a newly drilled well that had produced for 6 months, and had a 17 m completion thickness. The well was equipped with an ESP, without a packer, and fluids were injected through the annulus. An ASP volume of 70 m^3 was injected, and was followed by a 20 m^3 tracer plus 80 m^3 brine chase over a period of one day. The injection rate of the ASP slug ranged between 80 and 125 m^3/d. The well was shut-in for 3.5 days, after which a total flow-back volume of 187 m^3 was recovered over 1.5 days. A second, larger tracer test was also performed. Remaining oil saturation was determined to be 23%.

Petroleum Development Oman (PDO) – Onshore Oman

Stoll et al. (2010) and Oyemade et al. (2010) detail the chemical EOR ASP flooding project for an onshore, giant sandstone reservoir in Oman. The project workflow started with chemical formulation design using laboratory phase behavior experiments, core flood validation of formula performance, and five SWCT test pilots in three different fields. The first two SWCT tests were run different parts of a relatively heavy oil high-quality sandstone reservoir, the next two in two different formations of a medium oil high quality sandstone reservoir, and the last SWCT test in a tight carbonate reservoir (Stoll et al., 2010). During the SWCT tests, an inverted five-spot multi-well pilot test was being planned.

Laboratory phase behavior experiments were used to find a well performing chemical formulation, and the ASP formula used in the core flood ultimately contained 0.3 wt% surfactant, 1 wt% sodium carbonate, enough polymer to give 27 cP viscosity, and possibly other electrolytes. For the core flood, a 30 cm long and 5 cm diameter sandstone outcrop core was used. The flooding sequence started with a 2.2 PV water flood, followed by a 0.3 PV ASP slug, and ended with a 2.6 PV polymer drive. The oil bank was recovered from 0.4 to 1.2 PV after ASP injection began, with surfactant breakthrough occurring at 0.8 PV. Most of the 98% initially present oil was recovered during 0.4 and 1.2 PV of the injection period (Stoll et al., 2010).

Stoll et al. (2010) and Oyemade et al. (2010) describe one of the SWCT tests, which was performed slightly differently compared to the Salym SWCT test described previously. First, a base-line SWCT test without an ASP slug was run to determine remaining oil saturation prior to any influence by chemical flooding. A 3000 m^3 water flood was followed by a 30 m^3 chemical tracer slug containing 1 wt% ethyl formate (EtF) as the chemical tracer, with 0.5 wt% normal propyl alcohol (NPA) to mark the slug. A

120 m^3 water slug followed to drive the tracer slug out 3 m from the wellbore. Also, both the 30 m^3 and 120 m^3 slugs were tagged with 0.25 wt% methanol (MeOH). A shut-in period of 2 days allowed for partial hydrolysis to form ethanol (EtOH), and a 1.2 day back production period. Results showed an average oil saturation of 28% by volume. After the base-line test, a second SWCT test was run containing an ASP slug and polymer drive. A 420 m^3 ASP slug was injected into the well followed by a 60 m^3 tapered polymer drive and 420 m^3 water drive. The large slug/drive sizes ensure the tracer following does not reach beyond the treated radius. For the tracer injection, volumes identical to the base-line test were used. Upon analyzing the tracer results, the average remaining oil saturation was measured to be 1%, with an uncertainty range from 0% to 6%.

Angsi Field – Offshore Malaysia

Manap et al. (2011) details the chemical EOR alkali-surfactant (AS) SWCT test design and implementation in the Angsi field located offshore Terengganu, Malaysia, in the South China Sea. Other details regarding any laboratory phase behavior and core flood experiments were not provided. This SWCT test differs from the others mentioned because sodium hydroxide (instead of sodium carbonate) is the alkali, reverse osmosis de-salinates the AS slug injection water (to 2,000 ppm), and polymer is not used, possibly because of the light oil (42 API and 0.3 cP). However, the SWCT test does not provide information on mobility control.

Manap et al. (2011) description of the SWCT test pilot workflow was similar to the workflows described for other fields, and consisted of the following four phases: water flood (to reduce near wellbore oil saturation to near residual) followed by baseline SWCT test, soft water pre-flush and AS slug injection, second SWCT test, and extended

flowback and sampling (salinity/chemical concentration profiles). Water flood injection salinity was 33,000 ppm (even though formation salinity was 8,000 ppm), and the pre-flush, AS slug, and post-flush salinities were all 2,000 ppm. This initiates a negative salinity gradient before the AS slug, but not necessarily after it. A 0.6 PV AS slug was used. Two separate series of tests were performed in two different wells. The results showed remaining oil saturation decreased in the first well from 0.16 post-water flood to 0.12 post-AS slug, and in the second well from 0.27 post-water flood to 0.14 post-AS slug. The study concluded that the chemical formulation could successfully reduce residual oil saturation, and detailed a one month workflow at which the SWCT test was performed (Manap et al., 2011).

MULTI-WELL PILOTS

There are several different types of multi-well pilots, and each provides a trade-off between de-risking benefit and time/cost. This section describes the various multi-well pilot types and concepts, the de-risking that different multi-well pilots can and cannot provide, and several different onshore and offshore multi-well pilot case studies.

Multi-well pilot types and concepts

The simplest multi-well pilot design contains only a single-well injection system with one or more observation and/or sampling (i.e. not full producer) wells. Chai et al. (2011) describes this as an ‘observation pilot’ that involves drilling an observation well with or without sampling capabilities near an injection well. An observation well is completed with fiberglass casing for both monitoring and measuring in situ fluids over time, with focus on de-saturation, chemical concentration, and emulsion production (Chai et al., 2011). Observation pilots expand the study area to the distance between the injection and observation wells, and much larger volumes of chemicals can be used in the

pilot. However, because fluids are not continually produced, sweep efficiency cannot be accurately determined, and oil sale-ability (through emulsion breaking and treating) cannot be assessed on a production scale with typical surface processing facilities (Chai et al., 2011).

The most typical multi-well pilot is a producing pilot that is single patterned (e.g. five-spot), although multi-patterned producing pilots (e.g. multiple five-spots) have been called pilots (Widmeyer et al., 1988). The most important aspect of a multi-well producing pilot for de-risking purposes is the continual injection and production of fluids. A basic producing pilot in a five-spot pattern (four injector wells, one producer well) will have well spacing and injection volumes smaller than a commercial five-spot. This reduces the time and cost of the pilot, while achieving all the de-risking objectives. The injection fluid design would be similar to a commercial-scale pattern, for example, consisting of a pre-flush, ASP slug, and polymer drive, and the ASP composition would follow the successful laboratory and/or SWCT test composition. Observation wells can also be drilled within a pilot pattern for fluid sampling.

De-risking

Multi-well pilots are generally able to assess all of the risk categories mentioned previously, although some multi-well pilots, such as an observation pilot, can only assess a few (Chai et al., 2011). A typical pattern pilot (e.g. five-spot) has a sufficiently long injection time (e.g. usually more than one pore volume) to assess both the initial injectivity and longer term injection conformance. Fluid recovery from a patterned flood can determine the chemical formulation effectiveness (e.g. for oil de-saturation) and approximate the sweep efficiency within the pilot area (which may be different from the entire field). Because of the continuous supply, mixing, and injection of chemicals and

continuous production, both chemical supply and handling logistics and oil sale-ability after surface facility processing (emulsion breaking, treating, separating, etc.) can be assessed. Also, scaling potential can be assessed because of the longer time frame of the pilot.

Observation pilots are more limited for de-risking, which is usually dependent on the number of observation wells present. If sufficient volume of chemical are injected, injectivity/injection conformance, chemical supply and handling logistics, and possible scaling can all be assessed. One observation well can assess chemical formulation effectiveness and give some indication of sweep efficiency, although more observation wells will provide a better assessment of sweep efficiency. However, because fluids are not continually produced, assessment of oil sale-ability (after surface facility processing) is likely limited to a laboratory setting, which may or may not be sufficient for de-risking depending on the oil properties and chemicals used. In general, multi-well pilots, particularly pattern producing pilots, are intended to provide sufficient assessment for decision-making and FID for a commercial-scale project.

Case studies

Salym Petroleum Development (SPD) – Onshore West Siberia

As is typical with a mature onshore oil field, the Salym field is currently under water flood, and ASP flooding is planned for tertiary recovery (i.e. incremental above water flood). A description of the chemical formulation design, core flood validation, and SWCT test for the Salym field was given in the previous section. Djik et al. (2010) details the multi-well pilot design and workflow, which provides a useful benchmark for developing a reservoir-to-market model for onshore ASP flooding. The useful

information for the pilot design includes the overall design and pattern configuration, injector/producer well design and operation, and surface facility design.

Pattern configuration

The current well configuration for the Salym water flood is a 1000 m by 1000 m nine-spot pattern, with a central injector surrounding producers spaced 500 m from one another. A two-stage pilot design was selected, where a small-scale five-spot pilot with 100 m outer well spacing is followed by a larger, development scale five-spot pilot with 500 m outer well spacing. Both five-spot patterns contain four injector wells and one producer well. All five wells for the smaller pilot were new, with a producer placed centrally within a quarter of the nine-spot pattern surrounded by four injector wells. For the larger pilot, only the centrally placed producer well was new, and the four injector wells currently exist from the quarter nine-spot pattern. In addition to injector and producer wells, two observation wells, one sampling well, and one coring well are planned, with positioning between the centrally placed producer and corner injector wells (Dijk et al., 2010).

Injector/producer design and operation

Information on the well design specifications can be obtained from Dijk et al. (2010). The pattern configurations described are sized with the intention to complete the pilot flood in less than a year. Therefore, injector/producer flow rates must be designed according to injection sequence specifications. The planned injection sequence is a 0.3 PV pre-flush of soft water (to buffer hard formation water from the ASP slug), a 0.3 PV ASP slug, a 0.5 PV polymer drive, followed by formation water. Therefore, at least 1.1 PV will be injected prior to formation water chase, and likely to obtain sufficient results.

Studies at Salym indicate that water injection was taking place under fracture conditions. For the ASP flood design, limited in-zone fracturing is tolerable and out-of-zone fracturing should be prevented. Nonetheless, fractures were considered when estimating the stabilized ASP injection rate. Injection simulation concluded that a 150 m^3/d rate could be done without fracturing out-of-zone and limiting in-zone fracturing. Given a zonal thickness of 10 m and porosity of 20%, the small-scale pilot would have a PV of 20,000 m^3, and a continual injection of 150 m^3/d would inject one PV in about four and a half months. Therefore, injecting at least a 1.1 PV sequence plus formation water chase while completing the pilot within a year should be feasible. The development scale pilot would take much longer because the pattern area is 25 times larger.

Surface facilities design

Dijk et al. (2010) describes the planned surface facilities for the pilot, and provides a chemical injection plant schematic. To avoid construction on the main central processing facility (CPF) for the field, pilot injector/producer facilities will be located on the well pad. Emulsion-breaking studies would be done in the laboratory, rather than installing emulsion breaking facilities in the pilot to obtain saleable crude. Separated pilot produced water and water flood produced water will travel in the same flow line to the CPF. More detailed information on general surface facilities design for a chemical EOR project will be described later in the chapter.

Petroleum Development Oman (PDO) – Onshore Oman

A description of the chemical formulation design, core flood validation, and SWCT test for the PDO fields considered for ASP flooding was given in the previous section. Stoll et al. (2010) describes the planning for a multi-well pilot design based on results from the laboratory and SWCT test work. A 75 m x 75 m inverted five-spot (1

injector, 4 producers) well pattern is considered for the first pilot, with the option for a second larger pilot by converting the four producers to injectors, and drilling four additional producers around the outside. For the smaller pilot, the injection schedule would inject the ASP slug and polymer drive within half-a-year, with an additional year spent for subsequent water injection. Expected production would be chemical breakthough after 0.3 to 0.4 years, with oil bank production completing after one year.

Mangala Field – Onshore India

The Mangala Field is located onshore in western Rajasthan, India, and only recently began oil production in August 2009 followed by water injection in January 2010 (Jha et al., 2011). ASP flooding is intended to begin on a large scale within several years, and a multi-well ASP pilot is currently underway. A description of the chemical formulation design, core flood validation, ASP pilot design, and general field development are summarized here to begin understanding the workflow for building a general reservoir-to-market model.

Several surfactant and co-surfactant combinations were tested, and included alkyl-olefin sulfonates (AOS), alkyl-benzyl sulfonates (AOS), and internal olefin sulfonates (IOS), with varying carbon chain lengths (15 to 28 carbons). Diethylene glycol mono-butyl ether (DGBE) was used as a co-solvent, soda ash (Na_2CO_3) as an alkali agent, and partially hydrolyzed polyacrylamide (PHPAM) as a polymer (with 28% hydrolysis and 20 million Dalton molecular weight) (Pandey, 2010). The formulation showing the best phase behavior and aqueous stability consisted of: 0.1 wt% C_{16} ABS, 0.1 wt% C_{20-24} IOS, 1 wt% DGBE, 2.75 wt% Na_2CO_3, and 0.6 wt% NaCl (Pandey, 2010).

Core floods were performed using both Berea sandstone and native-state Mangala cores. A prepared Berea core at 680 mD permeability contained 0.68 PV initial oil

saturation with synthetic Mangala brine. A 1.6 PV water flood reduced oil saturation to a 0.4 residual saturation. ASP flooding with a 0.3 PV ASP slug saw oil bank breakthrough at 0.2 PV, and reached a maximum oil cut around 70%. Emulsion breakthrough occurred around 0.8 PV, and the total residual oil recovery was over 98% for the chemical flood. For the native-state Mangala core flood, four cleaned Mangala cores of 1.5 cm diameter were assembled lengthwise to a total length of 30 cm. In the core flood, polymer concentrations of 3000 ppm and 2000 ppm were used for the ASP slug and polymer drives, respectively, and each contained a viscosity around 30 cP at 10 sec^{-1}. The dead Mangala crude oil at 62 deg C reservoir temperature contained a viscosity of 21 cP at 10 sec^{-1}. Several modifications to this chemical flood were also made, including a reduction of alkali to 2 wt%, and reduction in polymer concentration to 2500 ppm and 2000 ppm for the ASP slug and polymer drive, respectively. This reduced the viscosities to 23 cp and 30 cp for the ASP slug and polymer drive, respectively, which compromised mobility control. Additionally, all the surfactant was believed to have been adsorbed by the rock. However, recovery of residual oil was almost 90% (Pandey, 2010).

Jha et al. (2011) details the current multi-well pilot design. A 100 m x 100 m five-spot pattern with four injectors and one central producer is used, with three additional observation wells placed within the five-spot pattern as well. Following an initial water flood, three 5-month flow periods (~0.4 PV each) will occur, beginning with a polymer slug in un-softened water, followed by an ASP slug in softened water, and finally a polymer slug in softened water (Jha et al., 2011). Chase water will follow after the final polymer slug. The objective is to inject at about one PV per year in order to complete the pilot in 18-24 months. A skid-mounted mobile chemical mixing and injection unit is considered, with a maximum injection rate of 3,000 bpd (~480 m^3/d) distributed at 750 m^3/d (~120 m^3/d) for each of the four injector wells. The planned production from the

central producer would be 1500 bpd (~240 m^3/d) (Pandey et al., 2008a; Pandey et al., 2008b). A 100 m by 100 m five-spot area, about 35 m net thickness (40% net-to-gross of 60-100m gross thickness), and 25% porosity (from a range of 21% to 28%) would give a pore volume of about 100,000 m^3. An average injection rate around 275 m^3/d would be about 1 PV per year, well within the maximum injection rate of 480 m^3/d.

Rosland et al. (2010) discusses the overall Mangala field development, with brief mention of chemical EOR development, while Pandey et al. (2008a) discusses quantitative field-scale chemical EOR simulations for a sector model. The field development plan (FDP) has 18 well pads, with a total of 162 wells for a multi-well pad concept (Rosland et al., 2010; Jha et al., 2011). The multi-pad concept was chosen to reduce land requirements by 85%. Vertical wells from single pads would require development of about 700 acres, while a multi-well pad design reduces that to 100 acres, while also reducing the total well cost (Rosland et al., 2010). Each of the 18 well pads are designed for a maximum of 30,000 bpd oil, 51,000 bpd liquid, 50,000 bpd water, 14 production wells, 7 injection wells, and 18 to 24 total wells (Rosland et al., 2010). For the zone of interest for chemical flooding (upper reservoir containing ~10% of STOIIP), an inverted nine-spot pattern forms the water flood base case, and infill drilling (i.e. in the center of each nine-spot quadrant) gives a regular five-spot pattern for chemical flooding (Rosland et al., 2010). Pandey et al. (2008a) provides field-scale sector model simulations using 300 m well spacing in a five-spot pattern, which show incremental recoveries of 7-8% STOIIP for polymer flood and 15% STOIIP for ASP flood after about 20 years.

St. Joseph Field – Offshore Malaysia

The St. Joseph Field is located in the North Sabah region, offshore Malaysia, and is a mature field having begun production in 1982, crestal gas injection in 1996, and

horizontal smart well water injection in 2011 (Chai et al., 2011). ASP flood designs for offshore fields are rare, but gaining interest. Because of the high cost of offshore wells, conventional pattern floods for chemical EOR with a low producer-to-injector ratio and close well spacing are precluded (Chai et al., 2011; Du et al., 2011). In the St. Joseph field, the producer-to-injector ratio is over 7 with most injector/producer distances over 300 m; however, infill opportunities should be evaluated for full-field development.

A multi-well pilot was designed using one of the six existing horizontal injector wells located at the oil-water contact. A semi-confined pattern with one injector and two producer wells positioned in an acute isosceles triangle fashion was planned (Chai et al., 2011; Du et al., 2011).Two producer wells (one currently available and one to be drilled) are positioned about 215 m from the injector, with a new observation well in the middle about 60 m from the injector well (Chai et al., 2011). An ASP slug of 0.3 PV followed by a 0.3 PV polymer drive will be injected, with the observation and producer wells seeing a response after 5 and 12 months, respectively. Since total field water injection is currently at 60,000 bpd from six horizontal smart well completions, one injector will allow about 5,000 bpd.

Du et al. (2011) assessed several full-field development concepts for the St. Joseph project. Under the current water flooding/gas injection scheme, the ultimate recovery factor is estimated to be 45%. By infill drilling, an additional 7% incremental recovery would be expected. With polymer flooding, 13% incremental recovery is expected, and 20% with ASP flooding (Du et al., 2011). Selecting ASP flooding comes with risks, and a staged-development concept helps in de-risking, where an initial phase 1 will occur after the pilot phase, followed by a later phase 2 (Du et al., 2011).

FULL FIELD DEVELOPMENT

Full-field development of an ASP chemical flood project is a commercial-scale approach involving many well patterns, and generally follows a successful multi-well, single pattern pilot and a final investment decision. A commercial development may be phased for de-risking purposes, with different phases targeting different zones or field areas, or an earlier (e.g. first) phase may be a small-scale version of a larger, later phase. However, making any final investment decision for commercialization for an ASP chemical flood requires understanding the general framework as well as risks relating to surface and subsurface development. This section will overview surface and subsurface aspects of a full-field ASP development, providing case studies and field analogues, which will be summarized in a general reservoir-to-market workflow benchmark at the end of the chapter. Other more detailed development aspects in a reservoir-to-market model, such as scheduling, costs, etc., will be detailed in the next chapter.

SUBSURFACE ASPECTS

A reservoir-to-market modeling approach for a chemical EOR development requires an understanding of the various inflows and outflows of the reservoir, especially characterizing the injection/production well performance and well spacing. Expected injection and production well performance and well spacing and/or patterning can be obtained from multi-well pilot results, simulation studies, and/or analogue data. A simplistic approach used later is to develop injection and production well type curves that can be applied to all wells in a reservoir-to-market development model. Also, a commercial-scale well pattern/spacing can simply be replicated a number of times to cover a field area of interest. At the present time, analogue data from a full-field ASP project is rare, with the industrial ASP flood of the central Xing2 area in the Daqing oil

field being the best documented ASP project with more than 10 years worth of data (Hongfu et al., 2003; Hongfu et al., 2008; Rue et al., 2010; Chang et al., 2006). The details of this ASP flood analogue will be explained in the following sub-section, and ultimately used as a basic starting point when building the reservoir-to-market model as a benchmark for this study.

Onshore industrial ASP flood – Central Xing2 Area, Daqing, NE. China

Few large-scale ASP floods have been reported throughout the world, with China's Daqing field being an exception (Chang et al., 2006). Chang et al. (2006) summarizes eight ASP pilots that have been performed in Daqing, with the well documented central Xing2 area ASP flood being a multi-patterned test with more than 10 years of field data to date.

There are a total of 45 wells in the central Xing2 area, 17 injectors and 27 producers, configured in five-spot patterns (Hongfu et al., 2003). Of the 27 producer wells, 9 are central producers that are fully surrounded by four injectors, giving nine five-spot patterns to assess the field performance. A 250 m well spacing is used for each of the five-spot patterns. The remaining 18 producers are along the perimeter.

Hongfu et al. (2008) describes the ASP flooding sequence. The flood began in 1998 with a water flood pre-flush that lasted two years. In 2000, a pre-flush polymer slug containing 1400 mg/L was injected for one year. In 2001, an ASP major slug was injected for three years containing 1 wt% NaOH, 0.2 wt% surfactant, and 1650 mg/L polymer. In 2004, an ASP subsidiary slug was injected for two years containing 1 wt% NaOH, 0.1 wt% surfactant, and 1500 mg/L polymer. In 2006, a post polymer protective slug was injected for one year containing 1000 mg/L polymer, followed by 630 mg/L polymer for one year, and then by water flooding (Hongfu et al., 2008).

The oil recovery from the pilot was about 24% of stock tank oil initially in place., and the ASP flood showed an 18% incremental oil recovery above expected waterflood oil recover. During the water flood pre-flush and pre-flush polymer slug, the produced water cut hovered from 90% to 96% before reducing dramatically to around 70% during the main ASP injection (Rue et al., 2010). The water cut stayed between 70% and 80% during nearly the entire main ASP injection, before climbing slowly back above 90% during polymer and post-polymer injection (Rue et al., 2010; Hongfu et al., 2008). The decreased water cut during and following ASP injection shows the clear response to the ASP and polymer injection program.

Onshore multi-patterned ASP pilot – Lawrence field, Illinois, USA

A recent multi-patterned ASP pilot was implemented in 2010, and is located in the Lawrence field, Illinois, USA (Sharma et al., 2012). The field of interest exists in the Bridgeport Sandstone formation of the Illinois Basin, and has been undergoing waterflood for the past 60 years. Several pre-pilot testing was performed, which included laboratory phase behavior and core flood experiments, polymer injectivity tests, single well chemical tracer tests, and an interwell tracer test program (Sharma et al., 2012). The multi-patterned pilot consists of six 5-spot patterns, containing a total of 18 wells (12 injectors and 6 producers). Because the pilot was just recently started, the oil recovery and overall success is still yet to be determined. However, early results are promising, with the peak oil production rate being more than five times greater with the ASP flood than with the waterflood (Sharma et al., 2012).

SURFACE FACILITIES

Chemical EOR projects require various surface facilities, chemical supply, and logistical support beyond what an ordinary water flood does. Identifying the generalities

of these for both onshore and offshore environments can help define a benchmark when building a basic reservoir-to-market model, with the ability to update the model later when more details are known about a specific field development. The general categories considered for surface facilities are the following:

- **Raw material supply/feed:** includes sourcing considerations of material inputs (chemicals and injection water), such as off-site chemical manufacture, transport to the site, and on-site handling and storage.
- **Input/injection processing:** includes surface injection facilities for source water treatment (storage, softening, de-salination, etc.) and chemical slug preparation (storage, filtration, mixing, pumping, etc.)
- **Output/production processing:** includes produced fluid treatment facilities (emulsion treatment, heaters, oil/water separators, electrostatic coalescers, etc.)
- **Sale and/or disposal stream:** includes new/additional disposal wells for produced water, export pipelines, FPSO, or tanker truck for sale-able and/or disposal fluids

Generalized equipment costs and installation for several of the above categories should be considered for a reservoir-to-market model. Injection facilities are a major contributor to surface infrastructure cost and scheduling for a chemical EOR project, and are therefore detailed in the following subsections for onshore and offshore environments. Produced fluids processing can require major additional installations for, say, an offshore environment, or simple facilities augmentations in a mature onshore environment. Also, raw material supply and produced fluid sale and/or disposal can require expensive, time consuming pipelines or supply vessels for specific projects; however, these are usually project specific, and a more generalized approach can use

existing infrastructure with additional transport or disposal operating expenses. Therefore, logistics and risks of produced fluids processing, material inputs, and sale and/or disposal are discussed in the section following injection facilities.

Onshore Pilot – Viraj Field, India

Pratap and Gauma (2004) provide a schematic and description of an ASP injection plant for a chemical EOR pilot, which shows the basic facilities required for an onshore pilot in general. The plant is designed to inject 800 m^3/d total ASP or polymer fluid to four injectors. The injectors are located within four inverted five-spot patterns (i.e. 4 injectors, 9 producers) having 200-250 m well spacing. The basic components of the chemical injection plant are as follows:

- **Material feeds:** source water, sulfonate surfactant, alkali, polymer, biocide, oxygen scavenger, nitrogen (inert) gas
- **Storage tanks:** two 400 m^3 stir/storage tanks for source water, one 20 m^3 tank for sulfonate surfactant, one 20 m^3 tank for alkali, three 200 m^3 ASP mixing tanks, one 50 m^3 surge tank (before injection), and nitrogen blanketing storage/system
- **Filtration:** two filters each for incoming source water and outgoing, mixed, ASP or polymer fluid
- **Mixers:** one polymer dispersion unit, one static mixer for alkali/surfactant, and one static mixer for alkali/surfactant plus polymer. Chemical slugs are also mixed in storage tanks prior to injection.
- **Pumps:** Three filter pumps for source water (to pump through filtration units), one meter pump each for alkali and surfactant, three filter pumps

for the ASP/polymer slugs (to pump through filtration units), and two triplex pumps to inject ASP/polymer slugs into the injection wells

Pratap and Gauma (2004) describe the preparation process. Concentrated alkali and surfactant solutions are prepared in two separate tanks and then passed through a sand filter followed by a micron filter to remove particles. Meanwhile, water is treated with biocide and held in holding tanks, then pumped through filters and mixed with polymer (from a polymer dispersion unit) and oxygen scavenger along with concentrated surfactant and alkali in static mixers. The mixture flows into three tanks and are aligned in parallel – one for filling, a second for mixing and maturing, and a third for injection. Mixtures are generally agitated slowly for 6-8 hours to mature while being blanketed with nitrogen gas (to remove oxygen), then run through a micron filter prior to injection.

A similar schematic is shown in Bragg et al. (1982), but with an extra tank for co-surfactant, and additional source water storage receiving fresh water and produced brine along with water blending facilities. If source water is undesirably hard and/or saline, facilities for water softening and/or desalination would also be present.

Offshore Full-Field – St. Joseph Field, Malaysia

Offshore and onshore chemical EOR facilities have to perform similar operations (regarding material feeds, mixing, storage, filtration, and pumping), but offshore facilities have differences regarding scale, logistical support, containment, etc. Du et al. (2011) discusses offshore injection facilities for a full-field ASP project in the St. Joseph Field, and provides a schematic as well. This field is in water shallow enough to support fixed jacket structures, and therefore facilities can be located on jackets while others on a barge or mobile floating facility. A barge or mobile floating facility can be used to house the water treatment and chemical injection facilities, as well as other equipment (utility

system, power generation, accommodation, mooring, etc.), and can be sized for full-field development and expansion up to 30,000 bpd (Chai et al., 2011). Water treatment includes seawater intake, filtration, de-salination, de-aeration, and pressure boosting, while ASP chemical injection includes storage, mixing, blending, filtration, and pumping. Chemical supply logistics are important as well because of an estimated 390 MT per day of chemical requirements (Du et al., 2011). Along with facilities for injection fluids, produced fluid processing is also required. A fluid processing platform for emulsion treatment, oil/water separation, and water disposal (which can include heaters, electrostatic coalescers, etc.) would also be required.

Although there are currently two injection platforms for the horizontal smart well injectors, the chemical EOR project requires two new well wellhead platforms bridge-linked to the existing ones. This will accommodate new infill and produced water/waste disposal wells. A produced water disposal pipe from the new processing platform to one of the new drilling jackets is required as well. The pilot required topsides modifications for tie-ins of wells (injector, producers, and observation), which will likely occur for the field development as well.

OTHER SURFACE/SUBSURFACE RISKS AND CHALLENGES WITH CHEMICAL EOR

Any oil and gas project will have risks and challenges, but because of the increased complexity and lack of commercial-scale analogues, chemical EOR projects can have several additional and/or different risks and challenges. Several studies discuss chemical EOR surface and/or subsurface risks and challenges for onshore and offshore environments, how they can be de-risked, and keys to success (Weatherill, 2009; Raney et al., 2011; Du et al., 2011; Chai et al., 2011). A previous section discussed several key de-risking areas for piloting, which for the subsurface included: chemical formulation

effectiveness, sweep efficiency, injectivity/injection conformance, and scaling; and for the surface included: produced fluids sale-ability and/or disposal, and chemical supply and handling logistics (Chai et al., 2011). Although all of these main risk categories are still important on the commercial-scale, there are additional risk considerations for large-scale chemical EOR projects addressed in the literature.

Surface and operational risks and challenges

There are several other surface and operational risks in addition to those discussed previously. For example, chemical EOR candidates that are mature fields have often been producing for decades, and nearing the end of their water flood lifespan. More importantly, they may be at the end of their facilities design lifespan, and, particularly for an offshore environment, extending the existing pipeline, platform, and facility lifespan may be expensive and required for safety purposes (Du et al., 2011).

The issue of supply logistics can be a challenge for projects, especially since fields can be in remote locations, or in areas prone to poor weather (winter temperatures, offshore storms, etc.). A large supply of chemicals is a transport, handling, and storage challenge, as well as the consistency of manufactured chemical specifications. Custom designed surfactants are not mass-produced and readily available, especially in the large volumes required for a field-scale project, in possibly a remote onshore or offshore location (Weatherill, 2009; Du et al., 2011).

There are a variety of chemical use and handling risks, particularly with respect to performance. Polymer, for instance, is commonly supplied in powder form; however, its hygroscopic nature can pose challenges in some climates using pneumatic transport and silo storage (Weatherill, 2009). There is a risk of shearing during polymer mixing, which can be minimize by avoiding centrifugal pumps, choke valves, and turbine meters for

example. Oxygen and iron cause of risk of destabilizing polymer, which is mitigated through the use of oxygen scavengers, corrosion-resistant alloys/non-metallic materials, de-aeration of source water, and nitrogen blanketing in mixing tanks (Raney et al., 2011). Raney et al. (2011) also discusses how polymer can experience a "cloud point," where polymer precipitates out of solution as a waxy solid, which can be caused by elevated temperatures and/or divalent ions (Zaitoun and Poties, 1983). Separation of oil-water emulsions and settling with viscous fluids is enhanced by heaters, although there is a risk of destabilizing polymer and compromising equipment/facilities function. Keeping facilities temperatures below 70 deg C can help mitigate this risk; however, separation time would take longer than at higher temperatures (Raney et al., 2011).

Because chemical EOR is not commonplace in the field, finding skilled or trained operators and laboratory personnel may be challenging. Additionally, offshore projects have space and weight limitations, and because wells are expensive to drill, large well spacing may be required, which can compromise sweep efficiency. Additionally, seawater is frequently the only available injection water source, which requires de-saliniation, softening, or de-aeration (Raney et al., 2011).

Subsurface risks and challenges

Chemical losses into and in the reservoir can be a major risk factor, and can occur despite whether a chemical formulation is effective or not. Loss of chemical may be difficult to diagnose until an expected oil bank with decreased water cut never materializes, which can normally be after about 0.5 PV of injection. By this time, a lower salinity polymer drive is being injected, and adding additional alkali/surfactant would be expensive (cost of additional chemical), uncertain (further losses may occur, additional chemical surface supply logistics), and technically unsound (because of salinity gradient).

One type of loss could be chemical degradation from the surface into and in the reservoir. Extensive laboratory testing for temperature stability, oxygen or bacterial induced degradation, and other factors are performed, and additional chemicals (biocide, oxygen scavengers, etc.) are included to de-risk most these problems. Other chemical loses in the reservoir can be from injection fluid loss through reservoir heterogeneity (high-permeability streaks and/or fractures, etc.), chemical adsorption onto rock surfaces, or chemical partitioning into an adjacent aquifer. De-risking of these can occur through accurate reservoir characterization and dynamic reservoir modeling, adsorption testing in the laboratory, and assessing pilot results.

DEFINING A RESERVOIR-TO-MARKET WORKFLOW BENCHMARK

As discussed previously, when building a reservoir-to-market model for a particular ASP flood project of interest, the information to build the model may come from a variety of different sources such as multi-well pilot results, simulation studies, and/or analogue data and other external sources. If the model is constructed early in the project lifecycle for screening purposes, multi-well pilot results and extensive simulation studies may be non-existent, and a greater reliance on analogue data and other external sources (e.g. industry knowledge, vendor information) is required. Aside from information used to construct the reservoir-to-market model, having an existing framework in place to serve as a reservoir-to-market model benchmark is very important as well. This section describes the usefulness of a reservoir-to-market benchmark, and the various steps used to develop a benchmark when considering the general subsurface/surface information provided previously. A detailed development and testing of a reservoir-to-market model benchmark (including scheduling, costs, etc.) will be given in the next chapter.

DEFINING SURFACE FACILITIES

A reservoir-to-market model representative of an actual chemical flood will contain general information on surface facilities, ideally relating to facility type, sizing, scheduling, and cost. However, very early in a project lifecycle, many specific details of this facilities information may not be known. Also, because facilities costs and scheduling are not marginal, it is important to identify and capture the essential facilities in the model, and assign reasonable estimates of costs, sizing, and scheduling from analogue and/or vendor data. Several key facilities to consider in project design include: source water treatment, chemical mixing and injection, production testing and processing, and other supporting facilities (e.g. pumps, storage tanks, pipelines). The chemical EOR project may be applied to a field already undergoing water flood with some existing facilities (e.g. pipelines, water and oil treatment, gas compression, storage tanks, etc.); however, significant additional facilities and even existing facilities replacement are likely given the added complexity (e.g. of required source water specifications, chemical mixing, emulsion treatment/separation, and oil sales specifications).

Source water treatment

The source water that will mix with the injection chemicals will often require treatment to meet certain specifications. These water specifications are usually identical and/or similar to water used in successful laboratory phase behavior and core flood experiments, SWCT tests, and/or pilot tests. Often the chemical formulations used in laboratory phase behavior and core flood experiments will be designed with the source water in mind to reduce the amount of treatment required. Source water can come from a variety of sources such as a near/on-site subsurface aquifer or river water, produced water from water flooding, and/or an external source delivered by truck or pipeline. Although produced water from an ASP flood is possible, the presence and varying concentrations

of residual chemicals can make treatment complicated and expensive, and risk flood performance compared to a consistent and predictable source water composition.

Treatment of source water can address suspended solids, oxygen, iron, bacteria, pH, salinity, and hardness among other things. Gravity clarifiers (for larger solids) and/or multimedia filters (for smaller and/or flocculated solids) can remove solids initially in the source water, or solids, such as iron compounds, that are flocculated using chemical flocculating agents (pH adjustment can also cause compounds such as iron to be insoluble). The majority of oxygen can be removed through vacuum de-aeration and/or gas stripping, with the final, smaller concentrations removed with oxygen scavengers such as sodium bisulfite (exclusively using high sulfite concentrations for oxygen removal, which converts to sulfate, can lead to reservoir souring by encouraging sulfate-reducing bacteria). Biocide chemicals can be added at points during the water treatment process to eliminate or prevent bacteria, and caustic agents can help adjust the pH. Both bacteria elimination and pH increase can be favorable for chemical stability (e.g. surfactant) during later chemical mixing. Other common treatment options can deal with water hardness and salinity, which include softening and de-salination (through nano-filtration and reverse osmosis), or salination if source water has too low of salinity (for an effective negative salinity gradient chemical flood). Cartridge filtration is usually a final filtration step using a fine (1 to 5 um) filter before the treated, de-oxygenated source water is pumped to an oxygen-free (e.g. using a nitrogen blanket) holding tank. The exact types and arrangement of these facilities is determined by a facilities engineer during the front-end engineering time period of the project. Treatment facilities, such as those described, are commonly ordered from a vendor as packages.

Production Testing and Processing Facilities

Producer wells in ASP projects can produce oil, water and/or their emulsions as well as free and/or associated gas, and production facilities are designed to treat all those products. There is, however, very limited field data on commercial-scale treatment of ASP produced fluids. To complicate matters, ASP flood produced fluids and therefore their treatment facilities are field-specific because of the emulsified products that result from the specific chemical formulation designed for a particular field's crude oil. However, several general production facilities components can be considered during early ASP field design that will capture overall cost/schedule issues.

Produced fluids and free/associated gas from the wellhead are first heated (e.g. above the cloud point), separated of most free/associated gas, and somewhat demulsified. Both of these activities can be performed in an inlet separator (e.g. horizontal separator) with a heater (or the heater can be separated from separator). The separator can be sized according to a desired residence time and gas volume. Various chemicals to demulsify, de-foam, eliminate or prevent bacteria, and inhibit scale (e.g. tolerant of alkali-environment) can be injected in the stream as well. If sufficient gas volume is generated, a gas-compression system (with capabilities to separate trace amounts of liquid) can be installed for gas exiting the separator. The oil/water/emulsion fluids flow to a main emulsion treatment facility (generally at or near atmospheric pressure for onshore fields).

The main emulsion treatment facility provides additional demulsifying chemicals and residence time (e.g. 1-3 days) to further break/separate the oil and water emulsion. Gravity separation allows top-exit of oil to an oil storage tank, bottom exit of water to a water skimmer, and middle exit of emulsion to an emulsion tank. Oil often needs further treatment to ensure sales specification as small amounts of ASP chemicals can be deleterious to downstream refinery processes. The oil can be heated (e.g. to destabilize

surfactant), mixed with demulsifiers (and given residence time) and wash water, and separated (e.g. electrostatic treater, centrifuge, etc.), then trucked offsite (or through pipeline if available). The water skimmer allows further residence time for waste oil separation, and water can be disposed of onsite (e.g. disposal well) or trucked for offsite disposal. An emulsion tank can provide further demulsifiers and even longer residence time. When emulsion is present in facilities, such as the inlet separator, main separator, and emulsion tank, a circulation pump is advisable to prevent emulsion locking.

A production testing facility is also necessary and is used to test produced fluids from wells about once per month. Because each well takes about one day to test, a test production testing facility can generally have around 25 wells associated with it. After fluids from a particular well exit the production testing facility, they combine with produced fluids from the other wells in the main production line that flows to the central processing facility.

Chemical Mixing and Injection Facilities

Chemical mixing facilities are specific to chemical flood projects as they pre-mix the source water, alkali/surfactant/polymer, and other chemicals prior to injection. Prior to chemical mixing, surfactant can be stored as a highly concentrated liquid solution (e.g. 20-50% active), and alkali as a solid (e.g. soda ash) or concentrated liquid). These chemicals can be diluted to less concentrated stock solutions and filtered prior to mixing with polymer in the main chemical mixing facility. More care is given to polymer mixing to ensure proper mixing and minimize or prevent shearing throughout the system (in fact, polymer cost allowances can be made to account for an estimated percentage of shearing and degradation). The common partially hydrolyzed polyacrylamide polymer is usually received as a powder, and then mixed slowly to a concentrated polymer solution.

Equipment designed for any subsequent pipeline transfer, pumping, and mixing of the polymer solution tries to focus on low shearing and prevent degradation of the polymer solution (e.g. positive displacement rather than centrifugal pumps). Surfactant, alkali, and polymer stock solutions ultimately feed into a main chemical mixing unit that combines and mixes an injection solution to the specifications designed for chemical flooding. Throughout the chemical system, prevention of chemical degradation from heat, bacteria, oxygen, iron, and other mechanisms is implemented through system design (e.g. low shear, low heat) and using various additives (stabilizers, scavengers, biocides, etc.). The final chemical formulation is pumped through a filtration system (e.g. 1-5 um) prior to injection).

Other supporting facilities – pumps, storage tanks, pipelines, etc.

Several other facilities that supply, connect, and transfer materials to and from the main facilities include storage tanks, pumps, and pipelines. Supporting and maintaining consistent performance of the entire system is the key design objectives of these facilities. For example, material tank size and quantity for particular material inputs is based on volume and frequency of external supply, and intermediate tank size/quantity (e.g. chemical injection fluid and treated source water holding tanks) can be based on potential maintenance downtown, supply and demand surges, etc. Even storage for waste disposal or oil export is based on frequency of pickup. Therefore, the amount of supporting facilities can be significant and extremely variable, especially from a cost perspective; however, detailed design and cost specifications may come later in the front-end engineering project period. Therefore, reasonable, conservative estimates are important when screening for project viability.

DEFINING SUBSURFACE AND WELLS

A reservoir-to-market model representative of an actual chemical flood will contain general information on the subsurface and wells; however, very early in a project lifecycle, many specific details of this information may not be known. The reservoir and wells are defined on both the surface (e.g. well patterning, well type) and subsurface (e.g. dimensions, pore volume, fluid phases, well trajectory), and delivering fluid from the subsurface to surface requires defining the well performance (e.g. injection/production type curves). Therefore, important categories that should be described include: field area and well patterning, reservoir dimensions and volumetrics, and well performance.

Describing well patterning in a reservoir-to-market model can be based on a pilot design, analogue data, or existing wells. The number of well patterns is determined from the total field area of interest and the area that a given well spacing demarcates per pattern. Reservoir volumetrics are determined from knowing net reservoir thickness, porosity, fluid properties, and oil saturation in addition to the field area. Often for a mature field, reservoir characterization can be fairly well understood; however, oil de-saturation during the chemical flooding process must be predicted to determine the amount of mobile oil. The depletion of this mobile oil volume during the chemical flooding process is determined by the well performance criteria described in the model. Type curves for injection and production wells obtained through simulation studies, analogue data, or piloting is a simple method to non-uniquely describe well performance. The type curves for each well can simply be added together to describe the total field performance, or if the total field performance is known from a multi-well pilot, type curves can be obtained by averaging the number of contributing wells. The next chapter will describe subsurface and well inputs in detail when building the benchmark reservoir-to-market model.

SUMMARY

This chapter provided an overview for identifying the reservoir-to-market workflow for a chemical EOR project, with a focus on project development strategies, de-risking, surface and subsurface concepts, and case studies. Understanding a basic project development strategy is important when identifying key components and risks and uncertainties of a reservoir-to-market model. A staged development concept was described, consisting of laboratory testing, piloting, and full-field development stages, at which feasibility, de-risking, and optimization could be assessed at each stage. Specific details and case studies were provided to further emphasize the workings of each development stage and associated de-risking, while building up to a full-field development framework. Surface and subsurface concepts and engineering were described on the full-field scale as well. A key message was that by identifying a reservoir-to-market model framework and workflow, a model can be built early in a project lifecycle and serve as a tool for assessing feasibility throughout project development from a combined economic, technical, and logistical perspective. Portions of the reservoir-to-market model can also be de-risked, updated, and/or optimized as data is gathered throughout the various stages, and the model as a whole can aid in decision-making as well.

CHAPTER 6: DEVELOPING A RESERVOIR-TO-MARKET BENCHMARK AND PERFORMING OPPORTUNITY VALUATIONS FOR A CHEMICAL EOR PROJECT

INTRODUCTION

A reservoir-to-market model benchmark for evaluating chemical EOR opportunities can be useful in the absence of commercial-scale projects to use as a benchmark that way as a standard or point of reference that can essentially be a starting point when screening or valuing a project. For example, if a reservoir-to-market model was created for a specific onshore US field of interest for chemical EOR, this model could serve as a benchmark for all onshore fields of similar nature, and simply be modified with known details specific to another field of interest. Even if a benchmark contains information from a variety of different fields, the fields should be similar enough to reasonably adapt the benchmark to another field of similar nature (e.g. onshore, light oil, thin-bedded, etc.). The idea of a benchmark is to be general enough to adapt to a wide range of fields, but specific enough to be accurate and make physical sense. For early project screening, the level of accuracy a benchmark offers is generally sufficient to screen a project, and progress it to the next phase for more detailed study.

Information (e.g. surface, subsurface, scheduling, costs, risks, etc.) for an opportunity can come from different sources such as multi-well pilot results, simulation studies, and/or analogue data and other external sources. However, if the model is constructed early in the project lifecycle for screening purposes, multi-well pilot results and extensive simulation studies may be non-existent, and reliance on analogue data and other external sources (e.g. industry knowledge, vendor information) is required.

This chapter will detail the development process of constructing a reservoir-to-market model benchmark, and test and validate the model by generating output of various

economic metrics for opportunity valuation and potential usage in chemical EOR project evaluation.

BUILDING THE RESERVOIR-TO-MARKET MODEL

The basic categories used to build a reservoir-to-market model were described in Chapter 2; they define the reservoir, well patterns, well performance, facilities (including pipe connections), rigs, scheduling, and costs. The reservoir-to-market model is essentially a production stream model that can be conceptualized as a hydrocarbon delivery system beginning with a source (reservoir) and ending with a receiver (export pipeline and/or refinery). Fluid is injected and/or produced from the reservoir according to well performance type curves, and is processed and delivered on the surface according to well and facilities patterns or layouts. The timeline of production and delivery occurs according to how many wells are to be drilled and how long this takes, facilities to construct, and the potential volumes that can be processed. Defining the various Capex and Opex of these items and processes along with the development and production timeline can ultimately generate economic output metrics with which to evaluate the chemical EOR opportunity.

For this work a benchmark model was created for an onshore, patterned development, and, for the reservoir, well pattern, and well performance inputs, the industrial ASP flood of the central Xing2 area (Daqing oil field) was used for reference given its extensive documentation (Hongfu et al., 2003; Hongfu et al., 2008; Rue et al., 2010; Chang et al., 2006). Several general assumptions for the benchmark model are based on the Daqing analogue, and using these assumptions helps qualify the analogue. One major assumption is that the injection sequence, volumes, and chemical concentrations of the Daqing analogue are reasonable and representative of a typical ASP

flood to be used as a benchmark. Additionally, the well spacing for the multi-patterned pilot is approximately 30 acres per five-spot pattern. Typically, a mature onshore field after infill drilling may have well spacing from 20 to 40 acres, and therefore the 30 acre spacing used in the Daqing analogue was assumed to be reasonable. Another assumption was that costs throughout the model period did not fluctuate or escalate, and were irrespective of oil price. In actuality, chemical costs and other Opex items fluctuate throughout a project life, and often have some correlation to oil price. Costs for a pilot, however, tend to fluctuate less given the shorter time length than a commercial scale project lasting several decades.

RESERVOIR AND WELLS

In the reservoir-to-market model, the reservoir describes the oil volumes that exist in the subsurface, and the wells describe the linkage between the subsurface and the surface. The reservoir is defined by various criteria (volume, fluids present, fluid properties, etc.) to reflect what type of volume is available for production. Various criteria (well patterns, type, performance, number, etc.) define wells to determine how the oil volumes will be extracted to facilities at the surface, and ultimately transported and sold to market. Delivering fluid from the subsurface to surface requires defining the well performance (e.g. injection and production type curves). This section describes basic reservoir and well inputs referenced from the multi-patterned Daqing central Xing2 area ASP flood, including subsections relating to: field area and well patterning, reservoir dimensions and volumetrics, and well performance.

Field area and well patterning

Well patterning for the benchmark ASP flood is shown in Figure 20 (modeled after Hongfu et al., 2003). A total of 9 five-spot well patterns were used containing 17

injectors and 9 central producers, with a well spacing of 354 m between producers. In addition, 18 peripheral wells surround the outer injector wells (Figure 20); however, neither the costs nor production from these wells is considered in the model. Each 5-spot pattern has an area of approximately 0.123 km^2, giving a total field area (only within the 5-spot patterns) of about 1.11 km^2 (Table 4), which will be discussed in the next subsection. Outside the pattern are peripheral producer wells, which are not accounted for in the overall produced fluid volumes in the model. These are important in a multi-patterned pilot to ensure pressure does not buildup adjacent to the 5-spot patterns to represent a large-scale commercial flood with dozens to hundreds of producer wells. The chemical costs will therefore be proportionally higher for this multi-stage pilot because the proportion that aids oil recovery from the peripheral producers is unaccounted for in this reservoir-to-market benchmark model.

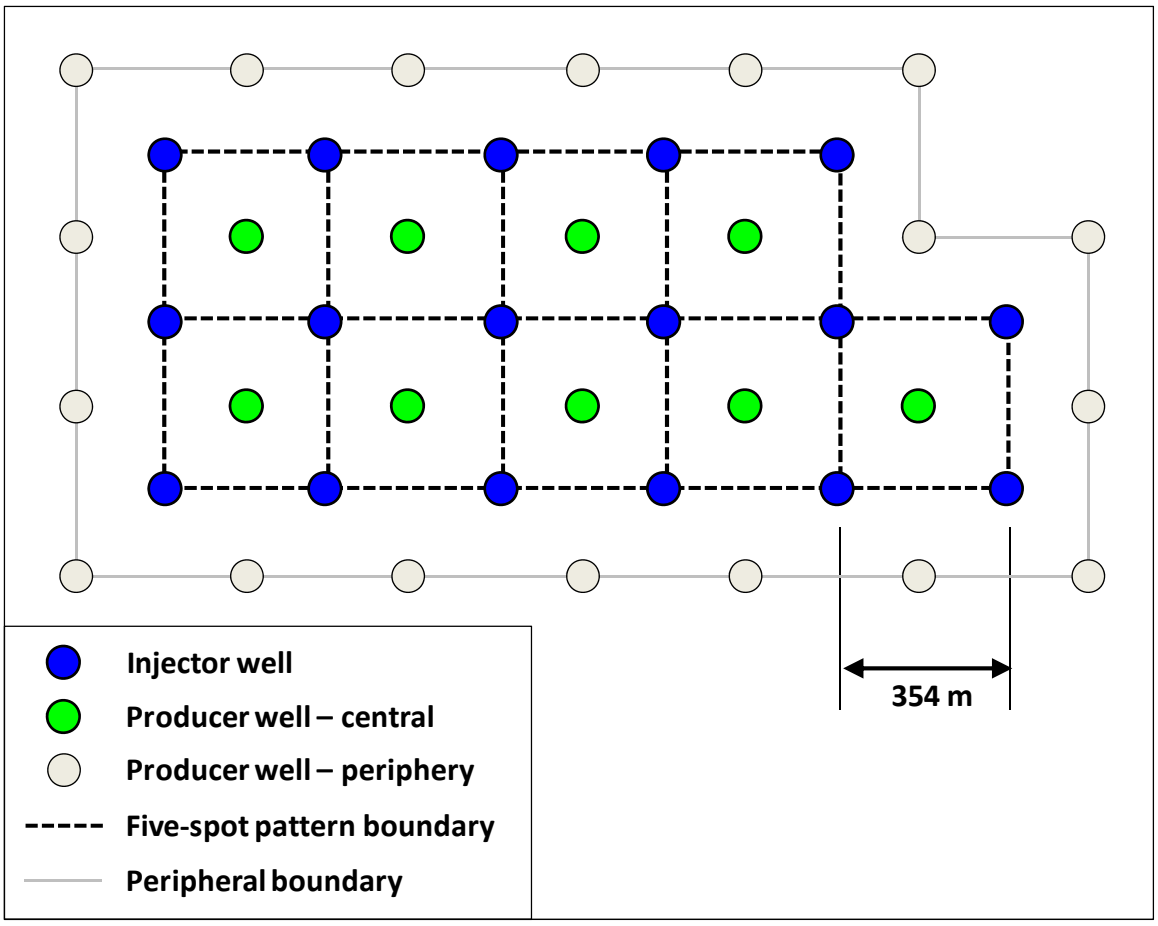

Figure 20: Well patterning for benchmark multi-patterned onshore ASP flood (modeled after Hongfu et al., 2003).

Reservoir dimensions and fluid volumes/volumetrics

Field and reservoir dimensions and volumes are in Table 4. As mentioned in the previous subsection, each of nine 5-spot well patterns contains an area of 0.123 km^2 (approx. 30 acres), giving a total field area of 1.11 km^2. The effective reservoir thickness is 7.1 m and the average porosity is 25%, giving a total static pore volume of 12.4 MM res bbl. Given an initial oil saturation of 72.3% and approximate formation volume factor

of 1.1 res bbl/STB, the STOIIP is calculated to be 8.15 MMSTB (Hongfu et al., 2003). The basic oil property description assumes an oil gravity of 35 API, and oil formation volume factor of 1.1 rb/STB. The gas-oil-ratio (GOR) is not considered in this study; gas volumes may be sufficient for separate processing facilities, compression, and sale, but this detail is left for more detailed study beyond reservoir-to-market screening (Table 4).

The basic model does not account for volume replacement in the reservoir (from injection, migration, etc.) or sourcing and migration parameters (such as fetch area, source thickness, generation efficiency, migration efficiency, trap timing, and seal integrity), and therefore contains only the basic volumetric parameters described previously (e.g. original oil in place and reservoir area). Oil is considered as the main fluid, with water and gas as subsidiary. Depletion of the oil volume initially present is modeled using production type curves, and the oil available to each producer is simply the total oil in the reservoir divided by the number of producers. In this simplistic reservoir-to-market model, the total oil volume merely acts as an upper bound constraint that is not actually exceeded in the model. Therefore, oil production is essentially controlled entirely by the production type curves, which describe the well performance of the producers. Similarly, water/chemical volumes injected and produced are also controlled by the injection and production type curves for well performance, and injection and production volumes are not materially related in the reservoir through material balance calculations. The reason for this is not only simplicity, but also that the Daqing analogue showed these well performance type curves were in fact feasible. However, a more detailed reservoir-to-market model could incorporate material balance, which was determined to be out of scope for this study.

Table 4: Field area, reservoir dimensions and volumetrics, and fluid properties for the benchmark model (referenced after Hongfu et al., 2003).

ITEM	CENTRAL WELL AREA (within 5-spot patterns)
Area and well info (Hongfu et al., 2003)	
Total Area, km^2	1.11
Number of 5-spot patterns	9
Area per 5-spot pattern, km^2 (approx. avg.)	0.123
Well spacing, m (between producers)	354
Total producers to injectors ratio	9 / 17
Reservoir volumes/properties (Hongfu et al., 2003)	
Avg sandstone thickness, m	9.9
Avg effective thickness, m	7.1
Avg porosity, %	25
Avg permeability, md	408.7
Pore volume, MM res bbl	12.4
Initial oil saturation, %	72.3
Oil FVF, res bbl/STB	1.1
STOIIP, MMSTB	8.15

Well performance

Type curves for an injector and producer well are shown in Figure 21, with the injector well injecting water and/or chemical formulation, and the producer well producing both water (e.g. with/without chemicals) and oil, without separate gas production type curves. This well data was obtained from Hongfu et al. (2008) and Rue et al. (2010) who provide about 11.5 years of field data covering all the planned injection cycles. Individual well performance curves are simply an average for each of the nine central producer wells of the total field performance (from all nine wells combined). Therefore, for simplicity, unique well behavior is undefined, which is generally not an

unreasonable assumption for a screening benchmark given that project screening is performed early in a project lifecycle when little may be known about ASP flood performance (note alternately, non-unique well performance could be obtained from a sector model simulation, and applied to each well in the full-field model).

The well performance/type curves in Figure 21 represent the water cut behavior described in Rue et al. (2010) for each of the chemical flooding periods. Early production data (during the water flood pre-flush and pre-flush polymer slug) shows produced water-cut ranging from 90 to 96% before reducing dramatically to around 70% during the main ASP injection. The water cut stayed between 70 and 80% nearly the entire main ASP injection, before climbing slowly back above 90% during polymer and post-polymer injection. The decreased water cut during and following ASP injection shows the clear response to ASP and polymer injection.

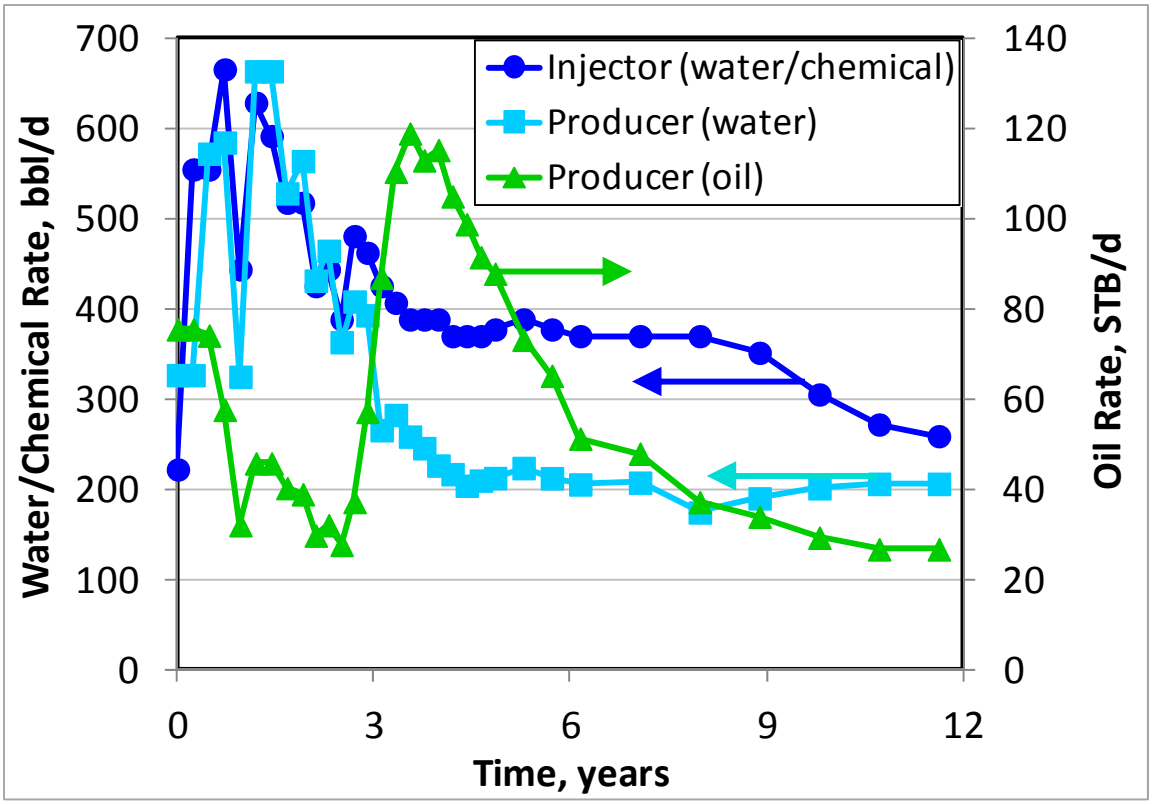

Figure 21: Fluid type curves for each injector and producer for a benchmark multi-patterned onshore ASP flood (data from Hongfu et al., 2003; Hongfu et al., 2008; Rue et al., 2010).

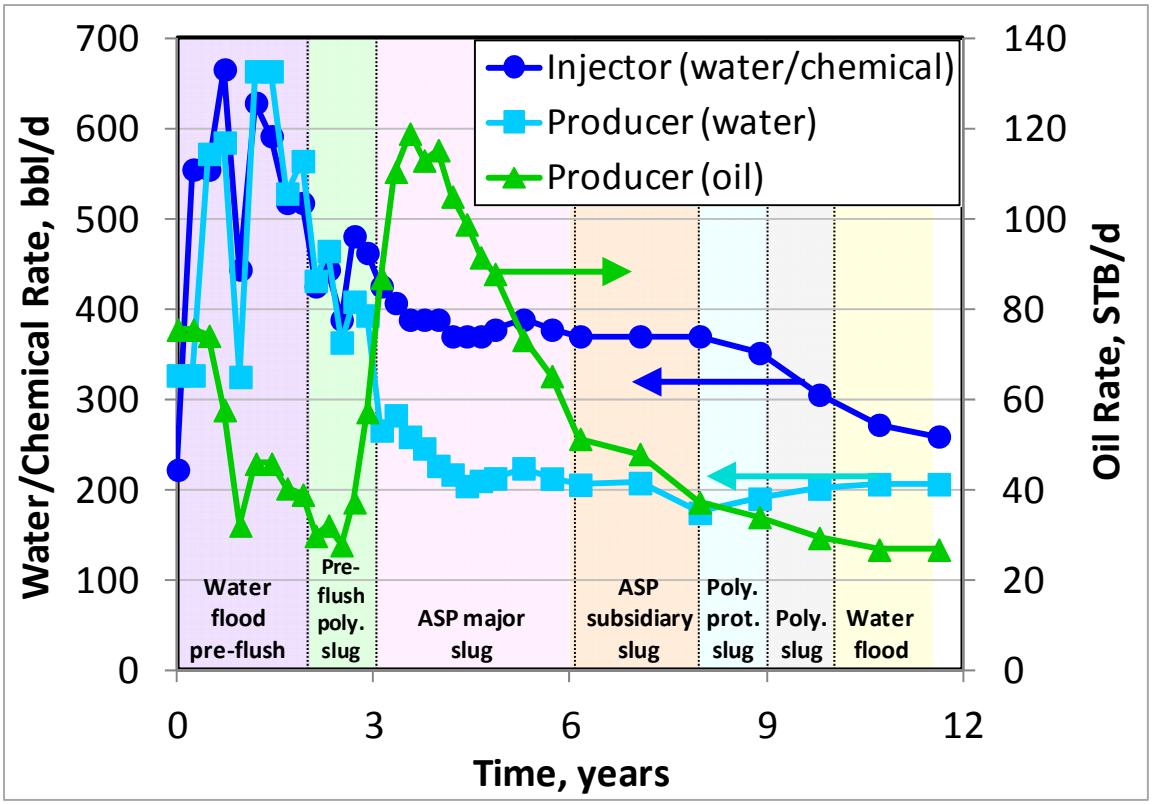

Figure 22: Flooding periods underlying the fluid type curves for each injector and producer well for a benchmark multi-patterned onshore ASP flood (data from Hongfu et al., 2003; Hongfu et al., 2008; Rue et al., 2010).

FACILITIES, PIPE CONNECTIONS, AND RIGS

General surface facilities layout

The general surface facilities required for a reasonably representative reservoir-to-market model were discussed in the previous chapter, and include: source water treatment, chemical mixing and injection, produced fluids test facility, production fluids processing, and other supporting facilities (pumps, storage tanks, pipes, etc). Figure 23 shows a general process schematic of the injection and production facilities layout and the material transfers throughout the system (specifics of supporting facilities are not

captured). The surface layout in the reservoir-to-market model created in PetroVR was based on the process schematic in Figure 23. Figure 24 shows how PetroVR represents the main surface facilities and their connections. PetroVR allows each of the items represented, their connections, and the fluids transferring between them to be specifically defined by various inputs (costs, scheduling, constraints, etc.), which will be detailed in the next subsection.

Although Figure 23 (as well as Figure 24) appears to consist of a single injection train and single producer train serving one injection and production well, respectively, the model runs quite differently. Wells are drilled or placed (i.e. if already drilled) in the model according to a specified number (26 total in this model – 17 injectors, 9 producers) and a specified producer to injector ratio (9/17 in this case given the five-spot arrangements), as shown in Figure 20. Facilities and pipes are specified as to a maximum well number and/or fluid throughput rate that can be handled. If these facilities were constrained to, say, the 26 wells in this model, and the field was developed with more than 26 wells, new facilities would be constructed once the 27^{th} well was initiated in the model. This allows for a large development scenario with hundreds of wells and dozens of facilities to be modeled according to real-world costs and schedules with inputting simple parameters for construction and drilling time, sizing (e.g. maximum fluid throughput rate or well connections) and costs for each item.

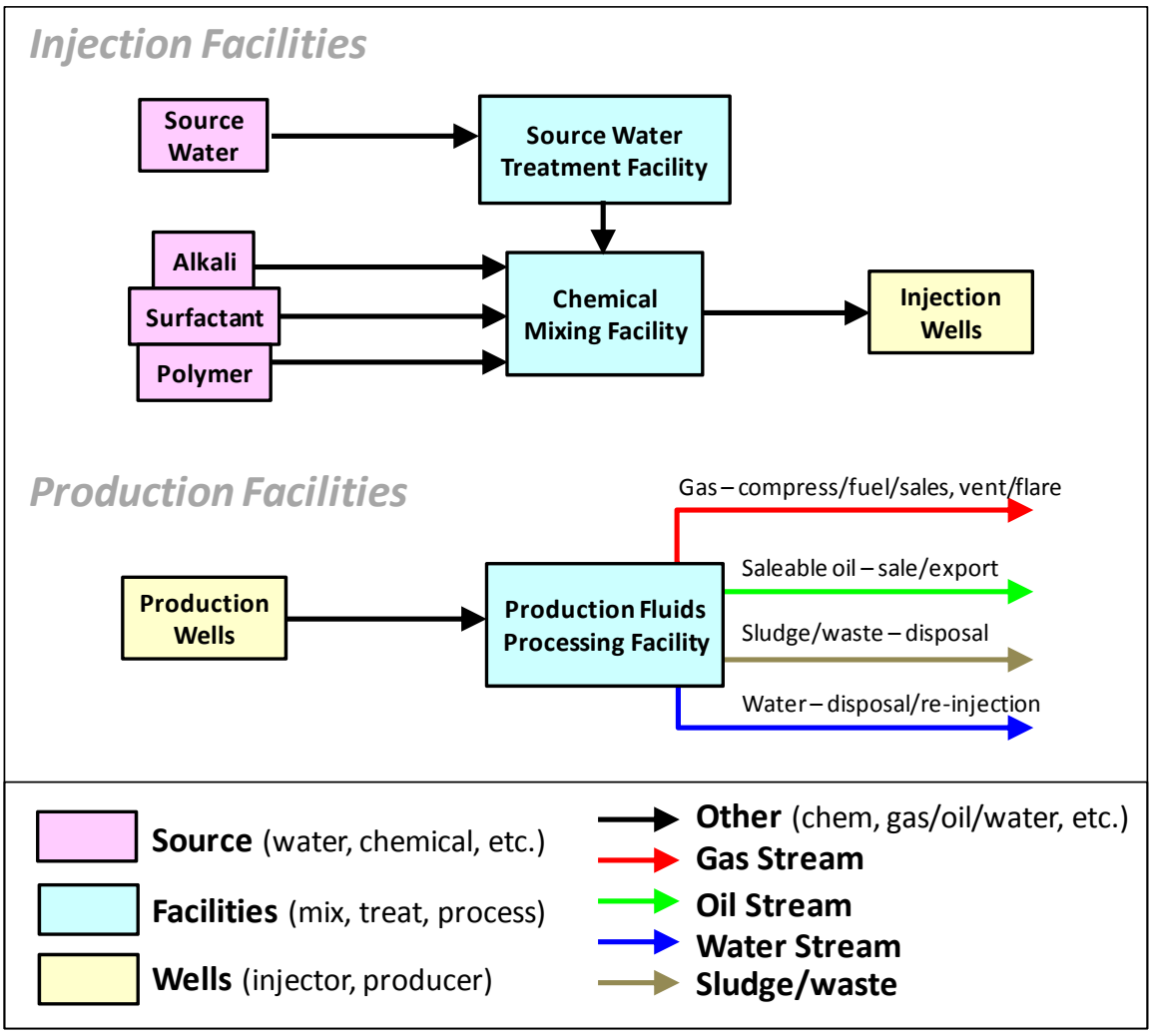

Figure 23: General surface facilities and process flow schematic considered for benchmark multi-patterned onshore ASP flood.

Description of PetroVR facilities layout

A simplistic method to construct a PetroVR model is to build a representative injection train and production train for the chemical EOR project of interest. Figure 24 shows how the injection and production trains are assembled in PetroVR. The injection train begins with a water source, represented in Figure 24 by a large tank. While water is

traveling through the injection train, it is mixed with various chemicals and additives at various times as specified by the chemical flood design. This chemical injection fluid and/or water then leave the injection train, and are pumped down injection wells at rates corresponding to the injection well type curves.

The flooding periods are next in the injection train, shown by source/receiver black boxes (although, in actuality, these may be storage tanks, pipes, etc.). A source/receiver in PetroVR can define fluid transfer during a particular time period at a particular unit cost. As will be discussed later, the injection period and cost information in Table 8 is defined for each of these source/receiver images. The source water treatment and chemical mixing and injection facilities are next in the injection train, and the scheduling, capacity, Capex, and Opex information in Table 5 are defined for each of these facilities. Last in the injection train are the actual injection wells. In PetroVR, injection well performance is described by the injection type curve in Figure 21, and other well information, such as costs, are defined in Table 6, and will be discussed later.

The production train defined in PetroVR is also shown in Figure 24, and begins with the production wells and a well pad. In PetroVR, production well performance is described by the production well type curves in Figure 21, and other well and well pad information is defined in Table 6 (to be discussed later). The produced fluids test facility and central processing facility are next in the train, and relevant cost and schedule information for these are described in Table 5. At the end of the production train are water disposal and oil export lines. An assumption is used that a disposal well is already in place, or that produced water is simply injected into some other portion of the field undergoing waterflood. An alternative would be off-site disposal through trucking, which would be more expensive. An oil export pipeline (or alternatively tanker truck pickup) is assumed to already exist, and will not incur any costs. Note also that a gas compression

and processing plant is not present in this model, as the reservoir is assumed to contain a negligible amount of gas; however, gas facilities could be easily inputted if desired.

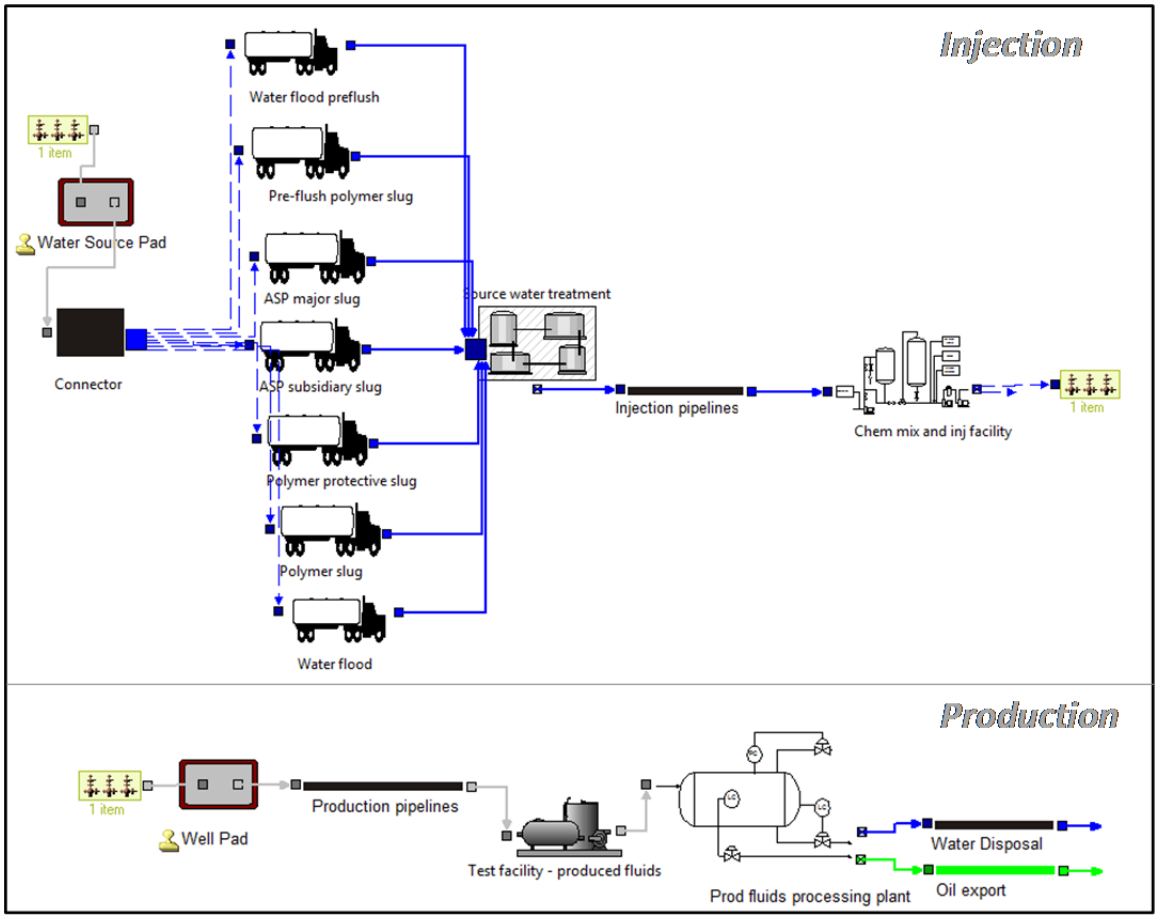

Figure 24: Construction of injection and production trains in PetroVR for the benchmark model. (printed from PetroVR model setup).

Connection pipe network

There are many supporting facilities such as tanks, pipes, and pumps that should be considered in the model. These supporting facilities are assumed to be captured in their respective general facility (source water treatment, chemical mixing and injection,

production test facilities, and production central processing facility) or well, and their individual costs and design and construction schedules are simply lumped in with the cost and schedule of the general facilities, if they do not already exist. The ASP flood considered for the model assumed an existing pipe network in place with the existing wells. The only new piping considered was recompleting injection wells with, say, plastic lined tubing to minimize chemical degradation from corroded iron and other deleterious products from the iron. A simplistic portrayal of the pipe connection network for the well pattern of interest is in Figure 25.

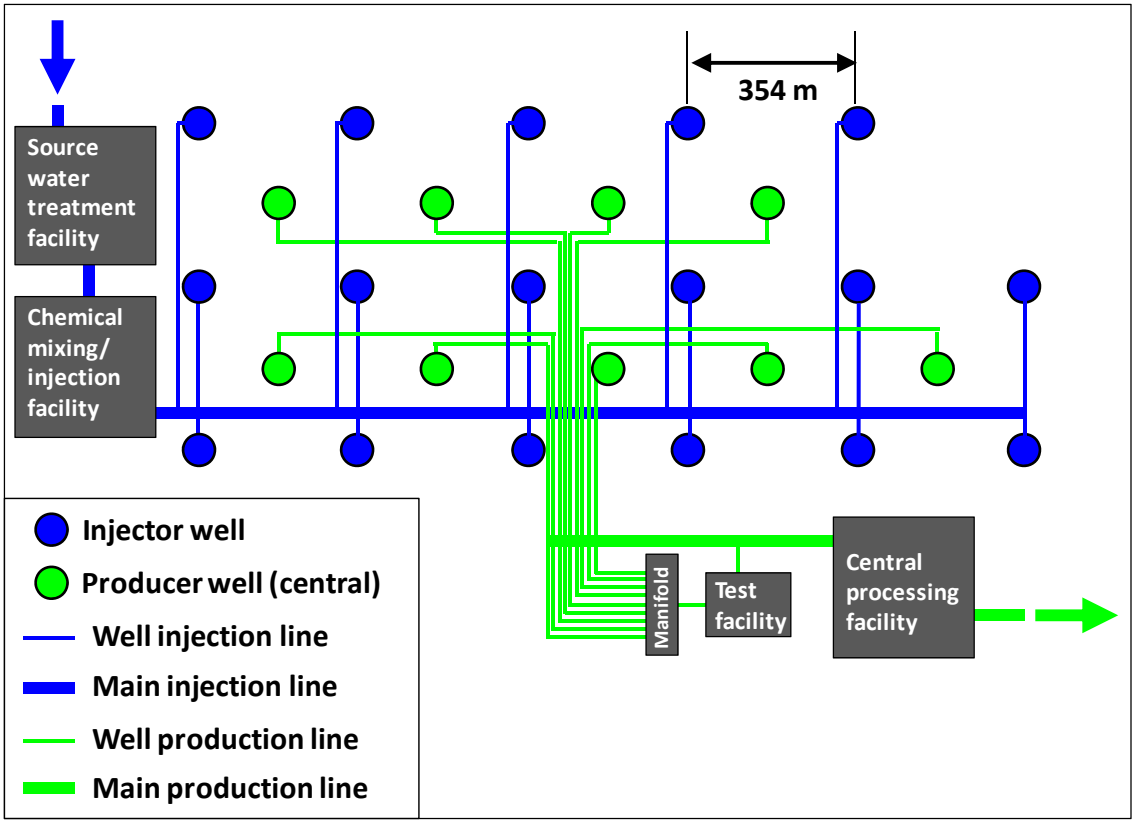

Figure 25: Approximation of pipe network and facilities for the benchmark ASP flood.

Rigs

Rigs are another surface input that is described in the model when accounting for drilling and completion time and costs during field development. A chemical EOR project in a mature field undergoing a water flood that uses existing wells will not require rigs for drilling new wells, but only completion rigs for performing scheduled workovers. When utilizing a completion rig, single rig is associated with a single well for a certain period of time to complete a job, and therefore more rigs tends to develop a field faster (subject to other constraints such as facilities construction and installation).

COSTS AND SCHEDULING

Wells, facilities, and materials costs and schedules are essential inputs for the reservoir-to-market model. General information on costs and scheduling can be obtained from discussion with vendors, investor reports, and journal articles (Pitts et al., 2004; Pitts et al., 2006; Wyatt et al., 2008). This section will detail the specific cost and/or schedule information used for the following inputs into the reservoir-to-market model: facilities, wells and rigs, chemicals, and injection.

Facilities costs and scheduling

The costs of the main facilities have been estimated from publically available investor reports and Wyatt et al. (2008). These are shown in Table 5. The general items in these tables include: source water treatment facility, chemical mixing and injection facility, production test facility, and production fluids central processing facility. A reference area to obtain typical costs would be a common, US onshore region with significant mature oil production. A reasonable, likely conservative assumption for each facility group is a design and construction time period of 365 days and a fixed Opex value of 3% of Capex per year for the facilities. All the facilities would be designed and

constructed concurrently, and therefore 365 days would essentially be the total length of time for facilities to be operational. Although some of the facilities can be purchased "off the shelf," the entire process of creating a basis for design, tendering, purchase and delivery, and installation could take about a year.

Wyatt et al. (2008) assessed 7 ASP plants of varying capacity, and estimated an ASP chemical mixing and injection facility to cost $3.4 million for an injection capacity of 5,000 bbl/d. Scaling up to the benchmark design of 12,000 bbl/d (given 17 injector wells and the type curves shown in Figure 25) gives an approximate cost of $8 million. In addition to the fixed Opex, a variable Opex for running the facility is assumed to be $0.05/bbl to account for power requirements and other minor expenses. The cost and size of a facility relative to a reference (from Wyatt et al., 2008) can follow a 1:1 ratio, as done here (e.g. twice the capacity at twice the cost). For upscaling, as performed later, the facility will be scaled up by a power rule using an exponent of 0.8 (e.g. twice the capacity at $2^{0.8}$ the cost). Rough approximations such as these are reasonable for screening criteria, and later in a project's life will cost engineers provide more detailed cost assessments (from cost databases, vendor quotes, etc.).

The production fluids central processing facility is also assumed to cost $8 million for a capacity of 6,000 bbl water/d and 1,000 STB oil/d, with an Opex of $0.50/bbl for any fluid or mixture (i.e. oil, water, emulsion, etc.). The source water treatment facility is assumed to be half the Capex at $4 million for a capacity of 12,000 bbl water/d. A variable Opex of $0.05/bbl will account for facility operation, such as power requirements. An additional variable Opex of $0.2/bbl will apply to the source water itself if being used of ASP or polymer slugs because of the cost for water treatment (softening, etc.). The source water will not have an Opex cost during the periods where

no chemical is injected. All facilities have a fixed Opex of 3% Capex per year to account for routine maintenance, repairs, inspections, etc.

Table 5: Estimated facilities costs for the benchmark reservoir-to-market model (from investor reports and Wyatt et al., 2008).

ITEM	VALUE
Facilities info	
Source water treatment facility	
Design/Construction time, days	365
Capex, $MM	4
Fixed Opex, %Capex/yr	3%
Water/injection capacity, Mbbl/d	12
Water Opex, $/bbl	0.05
Chemical mixing/injection facility	
Design/Construction time, days	365
Capex, $MM	8
Fixed Opex, %Capex/yr	3%
Water/injection capacity, Mbbl/d	12
Water Opex, $/bbl	0.05
Produced fluids test facility	
Design/Construction time, days	365
Capex, $MM	1
Fixed Opex, %Capex/yr	3%
Maximum wells per manifold	25
Central production processing facility	
Design/Construction time, days	365
Capex, $MM	8
Fixed Opex, %Capex/yr	3%
Oil capacity, MSTB/d	1
Water capacity, Mbbl/d	6
Fluids Opex, $/bbl	0.5

Well and rig costs and scheduling

The costs, scheduling, and other information for the wells and rigs are in Table 6. Table 6 notes 17 injectors, 9 central producers, and 18 peripheral producers. The 18 peripheral producers are not considered for production in the model, and are only noted as part of the original multi-patterned pilot in Hongfu et al. (2008). A well drilling time of 14 days and a well Capex of $0.8 million were used. The well fixed Opex is given as 3% of Capex per year, or about $24,000 per well per year. Well pad information includes a design and construction time of 30 days, one well per pad, Capex of $30,000, and a fixed Opex of 3% of Capex per year. Rigs that are used to drill the wells would incur a mobilization and demobilization cost of $0.5 million/rig and $0.25 million/rig, respectively, and the number of rig units used could be variable. However, for a mature field where wells and pads already exist, drilling rigs and pad construction would not be required, but the old tubing for each production and injection well must be replaced to prevent chemical degradation from old, corroded tubing. A tubing replacement job is assumed to cost $150,000 per well (rig included), and other costs for the existing well would be a fixed Opex costs of $24,000/year (3% of a new well Capex), as mentioned above.

Table 6: Estimated well and rig costs and other information for the benchmark reservoir-to-market model (from investor reports and Wyatt et al., 2008).

ITEM	VALUE
Well info	
Injectors	17
Producers - central	9
Producers - periphery	18
Well drilling time, days	14
New well Capex, $MM	0.8
Existing well tubing Capex, $MM	0.15
Well Opex, $MM/yr/well	0.024
Well pad	
Design/Construction time, days	30
Wells/pad	1
Capex, $MM	0.03
Fixed Opex, $Capex/yr	3%
Rig info	
Rig units	varies
Mobilization, $MM/rig	0.5
Demobilization, $MM/rig	0.25

Chemical costs

There are a few main chemical cost items considered for the chemical injection fluid shown in Table 7, which include alkali, surfactant, polymer, and source water. Sodium hydroxide (NaOH) was used as the alkali in the Daqing analogue study. However, the laboratory description in Chapter 3 details sodium carbonate (Na_2CO_3) as the common, preferred alkali. Scenario analysis in the next chapter covers a novel alkali scenario in the reservoir-to-market model. Table 7 also shows the unit costs associated with each item, as obtained in Wyatt et al. (2008). For ease of calculation, the source water cost can lump together both supply (trucking, on-site water well, etc.) and

treatment (e.g. source water treatment facility) costs. There are several other chemicals used in the injection and production surface facilities (biocide, oxygen and iron scavengers, demulsifiers, de-foamers, etc.); however, for the simplicity of this screening model, the costs of these additional chemicals are lumped in the general facilities operating and treatment costs, as their collective cost is assumed small relative to the key chemicals (alkali, surfactant, polymer, and water).

Table 7: Estimated chemical costs for the benchmark reservoir-to-market model (from Wyatt et al., 2008).

ITEM	VALUE
Chemicals, fluids	**Cost**
Alkali, $/lb	0.22
Surfactant, $/lb	1.85
Polymer, $/lb	1.2
Water treatment, $/bbl	0.2

Injection schedule

The injection schedule, described previously, is modeled after the workflow provided by Hongfu et al. (2008). Table 8 lists the injection schedule, or flooding sequence, and the respective material items used in each stage and the cost per barrel (assuming material costs described previously). The costs are not discounted as listed in Table 8; however, they are discounted in the model according to the point in time they are incurred. The first two years were a water flood pre-flush, with no cost associated with it because the water does not have to be treated and no chemicals are used. The third year was a pre-flush polymer slug containing 1,400 mg polymer/L, with an estimated cost

of $0.79/bbl. The fourth to sixth years was an ASP major slug containing 1 wt% alkali, 0.2 wt% surfactant, and 1,650 mg polymer/L, estimated to cost $2.96/bbl. The sixth to eighth year was an ASP subsidiary slug containing 1 wt% alkali, 0.1 wt% surfactant, and 1,500 mg polymer/L, estimated to cost $2.25/bbl. The eighth year was a post polymer protective slug containing 1,000 mg polymer/L, estimated to cost $0.62/bbl. The ninth year was another polymer slug containing 630 mg polymer/L, estimated to cost $0.47/bbl. The tenth year was simply a waterflood, with no cost associated with it. After 11.5 years, which was the length of available production data in Hongfu et al. (2008), the project was abandoned at an abandonment cost of 10% total Capex.

The cost per barrel for the chemical injection fluids generally accounts for the majority of the total cost of a chemical flood, and sensitivity in project profitability given cost fluctuations. Attempting to reduce chemical costs is usually the most common approach to making a chemical flood project profitable. The user of the reservoir-to-market model needs to account for a sufficiently wide uncertainty range around the expected value and costs per barrel for modeling chemical EOR scenarios. It is advisable to design a chemical flood early on using results from the laboratory phase, with optimum chemical quantities and/or concentrations to avoid unfeasibly high chemical costs later at the reservoir-to-market modeling phase, piloting, or even in the commercial phase. Once a baseline for costs and recovery are established and benchmarked, the reservoir-to-market model can be a valuable methodology to upscale to pilots/sectors and full-field implementation using a phase development approach.

The sequence and costs in Table 8 do seem like a rather elaborate process, given that a common ASP flood design has a pre-flush waterflood, ASP slug, polymer drive, and post-flush waterflood. Even the pre- and post-flush waterfloods may be optional, depending on waterflood and phase behavior salinities, and project completion,

respectively. More complicated design sequences are possible, and may occur during piloting (for benchmarking performance) and/or to save chemical costs (e.g. polymer concentration reduction in later chemical flood stages). However, for the purposes of demonstrating a reservoir-to-market model, the analogue data from the Daqing chemical flood was honored, which included the chemical flood sequence and well performance curves.

Another point of mention is the water treatment for the chemical flood at $0.2/bbl water, which assumes the water is treated and/or desalinated. Many chemical flood designs in the laboratory require a controlled salinity and hardness to be most effective. For example, certain types of alkali cannot tolerate hard water, polymer concentration needs to be increased (for the same viscosity) in higher salinity, and a surfactant slug performs optimally at a very specific, Type III optimal salinity value. Therefore, if a fresh water source is not available, incurring a high cost for treating source water may be worth the expense, although this should be modeled with different scenarios and/or sensitivities.

A last point of mention is the oil response to the pre-flush polymer flood. Figure 22 shows the oil rate begins increasing 3- to 4-fold, from about 30 STB/d at the end of the pre-flush polymer flood to about 120 STB/d during the ASP flood. Additionally, the oil rate remains high at well above 40 STB/d for several years (approx. 5 years) until the end of the subsidiary ASP slug. This clearly shows the response in oil production from increasing the viscosity of the injection fluid with polymer, and therefore improving the mobility and displacement efficiency. Furthermore, the response in oil production to the ASP slug is shown from the duration at which a higher oil rate is maintained.

As mentioned previously, the robustness of a chemical formulation is a priority to ensure that results observed in the laboratory or simulation may still be obtained in the field. Field conditions may be more variable and harsher in the reservoir than in the

laboratory, and a customized lab formulation may appear delicate. However, research has shown that design aspects such as salinity gradient, using multiple surfactants, and other factors help improve the robustness. The reservoir-to-market model may incorporate this robustness through flexibility of design and engineering to face changing real life challenges that may be encountered with chemical EOR in the reservoir.

Table 8: Injection schedule and sequence with respective material items and undiscounted costs per barrel for each flooding sequence for the benchmark model.

ITEM	TIME	
	AMOUNT/CONC.	COST ($/bbl)
Water flood pre-flush	**Year 0-2; 0.53 PV**	
Water	1 bbl	0
TOTAL	**1 bbl**	**0**
Pre-flush polymer slug	**Year 2-3; 0.23 PV**	
Polymer	1400 mg/L	0.59
Water	1 bbl	0.20
TOTAL	**1 bbl**	**0.79**
ASP major slug	**Year 3-6; 0.59 PV**	
Alkali	1 wt%	0.77
Surfactant	0.2 wt%	1.30
Polymer	1650 mg/L	0.70
Water	1 bbl	0.20
TOTAL	**1 bbl**	**2.96**
ASP subsidiary slug	**Year 6-8; 0.36 PV**	
Alkali	1 wt%	0.77
Surfactant	0.1 wt%	0.65
Polymer	1500 mg/L	0.63
Water	1 bbl	0.20
TOTAL	**1 bbl**	**2.25**
Polymer protective slug	**Year 8-9; 0.2 PV**	
Polymer	1000 mg/L	0.42
Water	1 bbl	0.20
TOTAL	**1 bbl**	**0.62**
Polymer slug	**Year 9-10; 0.15 PV**	
Polymer	630 mg/L	0.27
Water	1 bbl	0.20
TOTAL	**1 bbl**	**0.47**
Water flood	**Year 10-finish; 0.24 PV**	
Water	1 bbl	0
TOTAL	**1 bbl**	**0**

OTHER ECONOMIC INPUTS (OIL PRICE, TAXES, DEPRECIATION, ETC.)

Other economic input parameters besides Capex and Opex costs are necessary inputs for a reservoir-to-market model to calculate economic metrics to determine expected project valuation. Table 9 lists general economic inputs for the model, which are in addition to the cost inputs described previously. The item categories include oil price, quality, inflation, depreciation, tax, and royalty parameters among others, and all contain relatively common values for all items.

To test the model, the crude oil price is assumed to be $100/STB oil, and for simplicity, does not contain an API or sulfur content quality correction, or price inflation. Oil price modeling was explored previously in Chapter 3, and likely contains one of the largest uncertainties of all input parameters. In this section, the price was fixed at a constant value to explore the effects of other input parameter uncertainties; however, oil price models are incorporated into the reservoir-to-market model in later sections. Cost inflation is also assumed to be zero. Inflation would have escalated Capex and Opex items over time.

Regarding depreciation, all Capex items start depreciation as they are built, and they are depreciated using the straight line method over a 10 year period (approximate chemical flood lifespan in this case). There is assumed to be no salvage value. The federal and state income tax rates are assumed to be 35% and 5%, respectively, while the royalty and severance ad valorem are assumed to be 10% and 5%, respectively. The standard federal corporate income tax for the US is 35%, which is why this value was used. Additionally, although state income tax rates vary between states, a reasonable and representative approximate of 5% was used to demonstrate the expense a state income tax

would have on project valuation. The discount rate used for NPV calculations is assumed to be 5%.

Table 9: Economic inputs for the benchmark model, including oil price, inflation, depreciation, and tax information.

ITEM	VALUE
Oil price, quality, and price/cost inflation	
Crude oil price, $/bbl	100
API quality correction below 35 API, $/API	0
Sulfer quality correction, $/% sulfur/bbl	0
Cost inflation, %/yr	0
Price inflation, %/yr	0
Depreciation	
Depreciation period, years	10
Depreciation method	Straight Line
Salvage value, $	0
Start time	As Built
Depreciable items	All Capex
Taxes, royalities	
Federal income tax, %/yr	35
State income tax, %/yr	5
Royalty, %/yr	10
Severance ad valorem, %/yr	5
Discount rate, %/yr	5

RESERVOIR-TO-MARKET BENCHMARK MODEL SIMULATION AND RESULTS

Simulation results contained information on scheduling and project timeline, production and injection forecasts, and cash flow calculations and economic metrics. The following sections will explore further scenario and what-if analyses by using Monte Carlo simulation, scenario and decision tree analysis, and overall opportunity valuation.

SCHEDULING AND PROJECT TIMELINE

Figure 26 shows the schedule and project timeline followed by the reservoir-to-market model, with the various facilities construction and flow periods displayed, as well as cost information. During scheduling input, periodically displaying and visualizing a project timeline helps to assess the critical path for the project and whether various components (facilities construction, flooding periods, etc.) are phasing in and out in the proper project sequence.

ASP injection was initiated at a particular date (Jan 1, 1997) corresponding to time zero (project start). Immediately, the existing wells, water source, and sequence were defined. Next, the facilities and pipe connections were built, which, as defined by the feed plan, each take one year to design and construct. The oil export and water disposal ports are defined instantaneously in the facilities because their infrastructure already exists (e.g. a water disposal well and tanker truck making routine oil pickups). Once the wells, facilities, and pipe connections are defined or constructed, the flooding periods begin.

The timeline in Figure 26 shows each of the flooding periods represented that were listed previously in Table 8:

- The flooding periods follow the desired start and stop dates.
- After all the flooding periods occur, the project is scheduled to be abandoned, which marks the project's stopping point.
- Project abandonment is determined when cash flow is no longer positive, though other reasons can occur (lease expiration, facilities retirement, etc.).
- In the case of abandonment, the scenarios followed the completion of the Daqing analogue schedule.

The schedule and timeline shown in Figure 26 captures all the flooding periods and abandonment of the reservoir-to-market model.

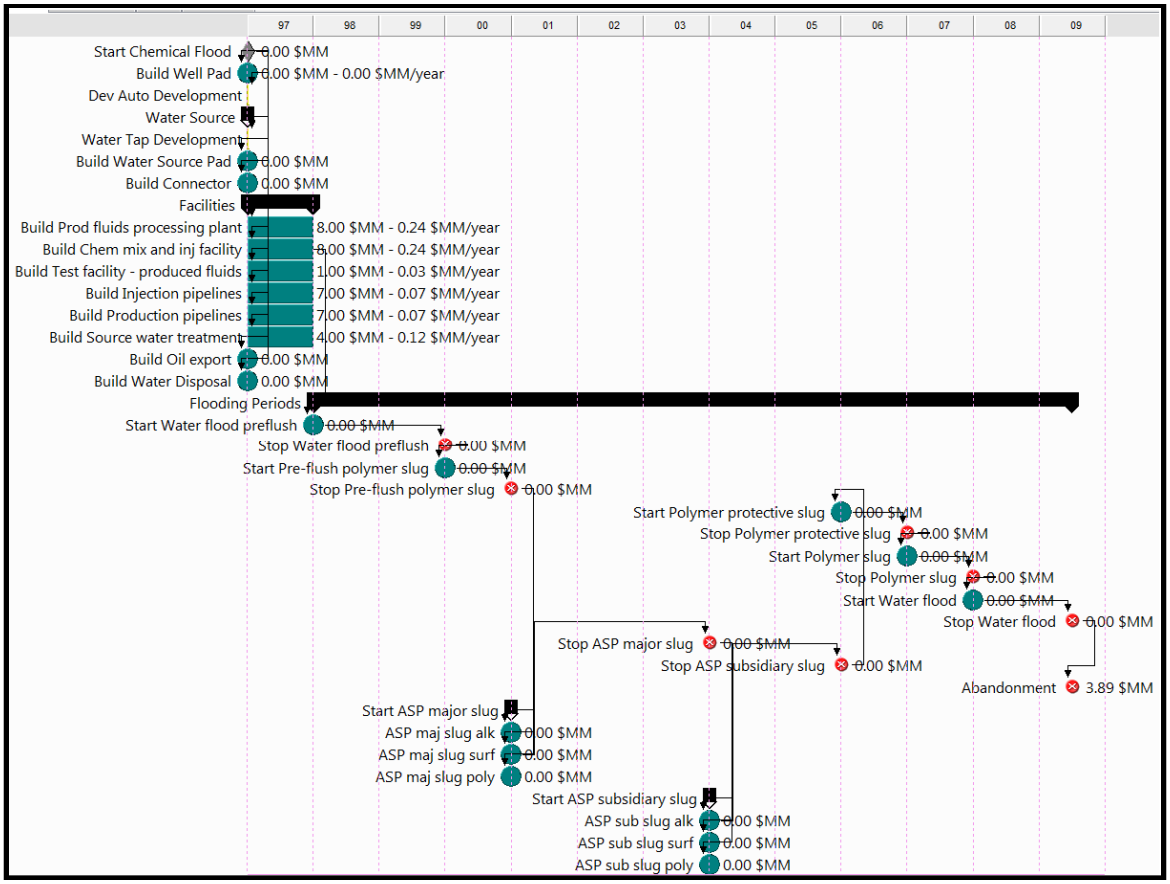

Figure 26: Schedule of the benchmark reservoir-to-market model (from PetroVR output).

PRODUCTION AND INJECTION FORECASTING RESULTS

The production and injection forecasting results matched the inputted type curve performances, subject to various constraints (e.g. facilities capacity). Facilities were planned to accommodate more than the maximum expected fluid injection and production, and were therefore unconstrained. Figure 27 shows the total injection and production rates of all wells combined over the project life. The curves are similar to the production type curves from Figure 21 because well performance was also unconstrained.

Similar to the type curves, the forecast results also show the total injected fluids to exceed total produced fluids by nearly a factor of two due to the higher injector to producer ratio. There are 17 total injectors in the model and only 9 total producers, roughly a two-fold difference.

Moreover, and similarly to the Daqing chemical flood, excess injection fluids would not cause pressure to build up in the reservoir due to production of excess fluids by the peripheral wells surrounding the injectors. For a multi-stage pilot, peripheral producer wells help maintain uniform performance between the different 5-spot patterns, representative of a much larger commercial-scale flood with dozens or hundreds of wells.

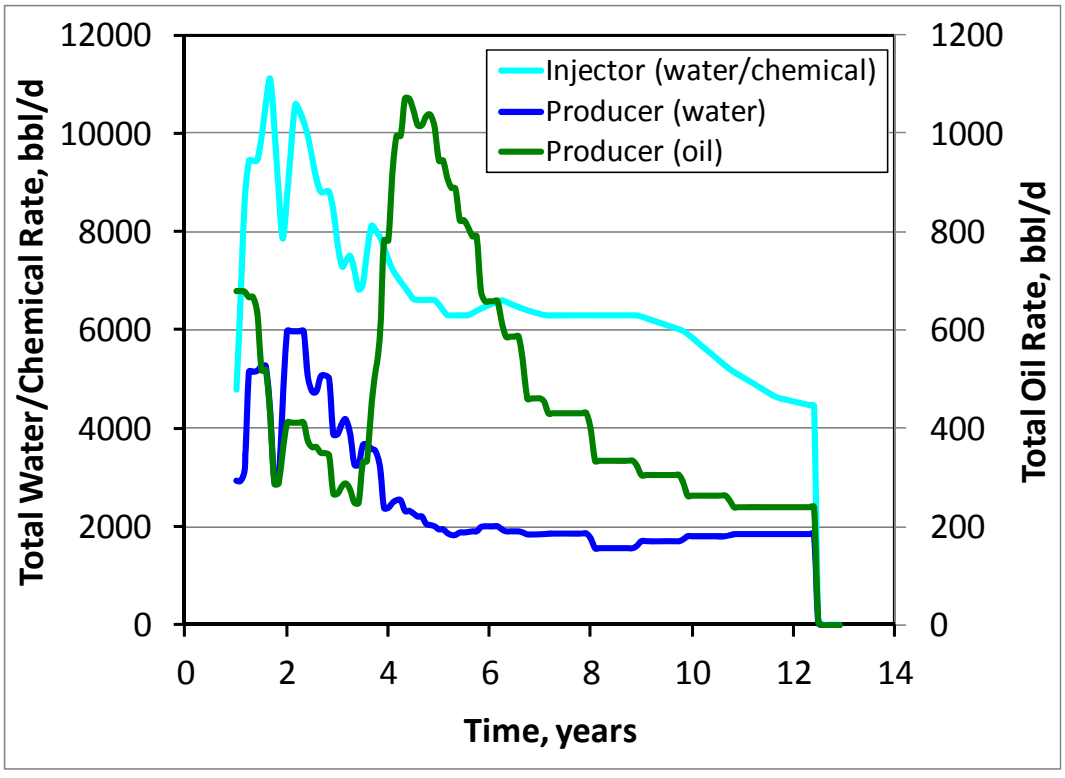

Figure 27: Benchmark scenario and forecast results for injection and production of pilot generated for the reservoir-to-market model.

ECONOMIC RESULTS AND METRICS

The reservoir-to-market model focuses on the economic feasibility of a project, and assessment of potential financial scenarios. This section will show economic output data and analyses typical to business financials, and investigates potential outcomes for: revenue, royalty, severance, Capex, Opex, earnings before taxes, loss carry forward, taxable income, federal and state income tax, cash flow, and economic metrics (NPV, IRR, UTC, VIR, and payback period). Most of the data is undiscounted, except for the discounted cash flow and economic metrics.

Revenue, Royalty, and Severance

The total revenue, royalty, and severance tax results generated by the reservoir-to-market model are in Figure 28. The revenue curve has a trend similar to the oil production curve in Figure 27, except the oil production rates are converted into dollars using a $100/STB oil price. As mentioned previously, the oil price is assumed constant at $100/STB throughout the project life. Royalty and severance were assumed to be 10% and 5% of the revenue, respectively, and therefore the curve of their summation is simply a scaled down version (e.g. 15% of the value of) the total revenue curve.

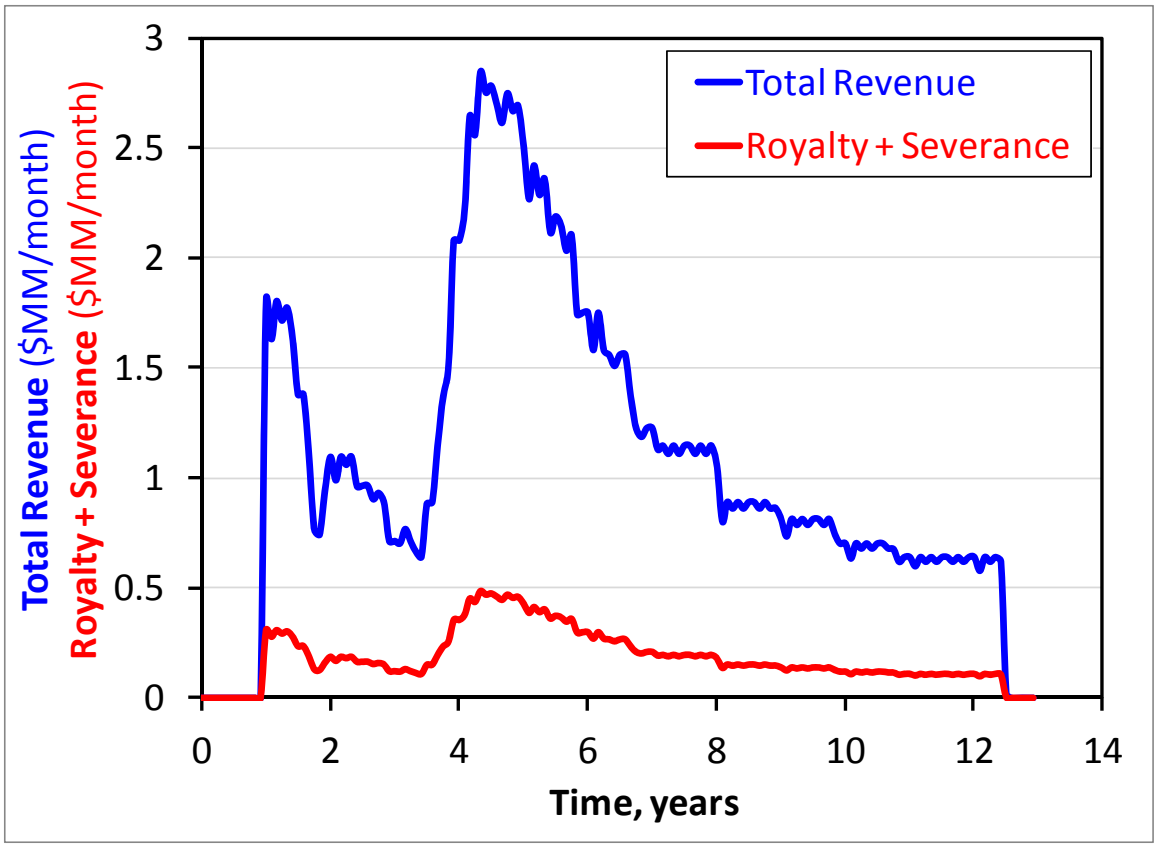

Figure 28: Total revenue, royalty, and severance tax results generated by the reservoir-to-market benchmark model.

Expenses – Opex, Capex, and Depreciation

The various expenses generated by the reservoir-to-market model are in Figure 29. They include total Capex, total Opex, and depreciation. The total Capex curve shows most of the Capex to accrue during the first year when the facilities and wells are being developed. The spike at the beginning accounts for all the well recompletions (i.e. tubing replacement) that were assumed to occur quickly, and the spike at the end is the abandonment cost (i.e. 10% of the total Capex items, which occurred in the first year). Field abandonment consists of several different activities, including: removing and

disposing/salvaging well equipment, production tanks, surface facilities, and pipes; plugging wells (e.g. with cement); and environmental cleanup and/or surface remediation.

The total Opex curve accounts for all the fixed Opex associated with the facilities and wells, as well as the variable Opex from the chemical flooding materials and fluids treatment (source water, injection fluids, and production fluids). The increases and decreases in the total Opex is caused by the changing unit chemical costs associated with the different flooding periods; otherwise the fixed Opex would stay relatively constant throughout the project life. This is better shown in Figure 30, which displays the variable Opex of the fluid inputs during each flooding phase. The total Opex curve in Figure 29 shows a similar trend to the curve in Figure 30. The depreciation curve in Figure 29 was generated using the straight-line depreciation method, which depreciates the Capex costs accrued during the first year over a 10-year depreciation period. The abandonment Capex item at the end of the project life cannot be depreciated as the project completes at that time. Values are undiscounted, and the total Opex has a ‘stair-step’ appearance reflecting the changing chemical costs during different injection periods (as shown in Figure 30).

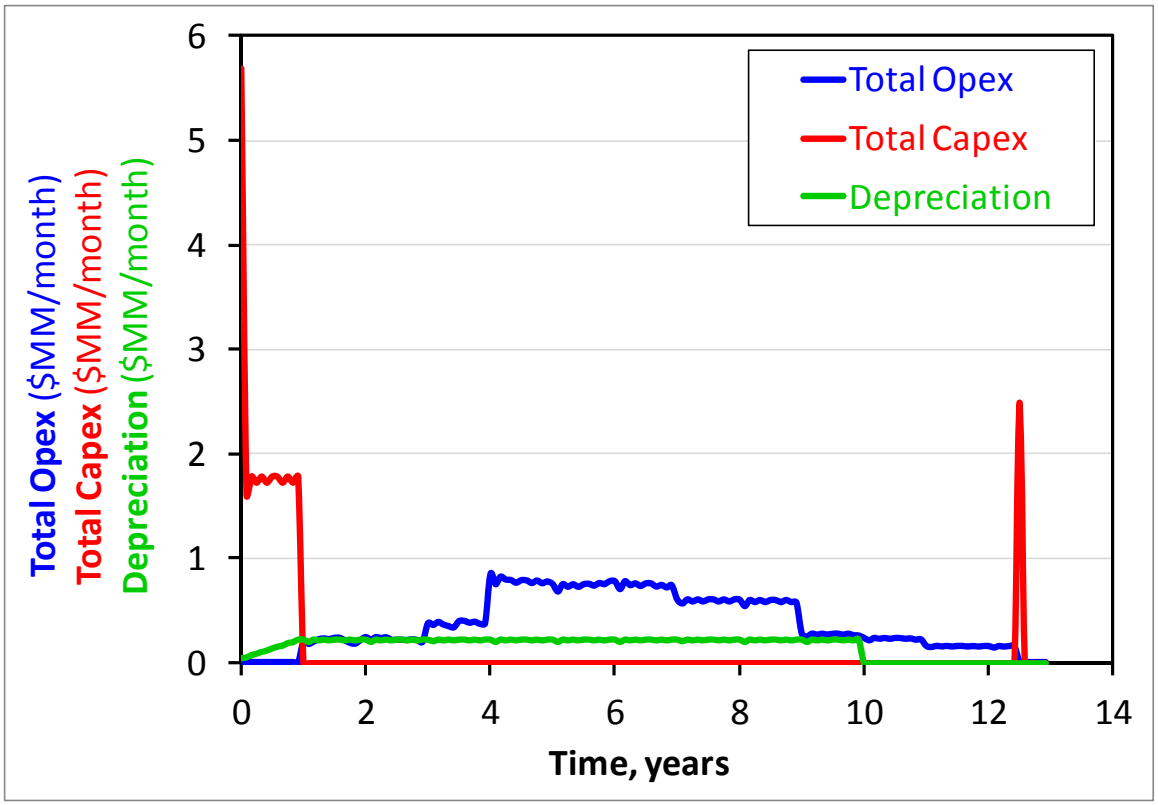

Figure 29: Total Opex, Capex, and depreciation results generated by the reservoir-to-market benchmark model.

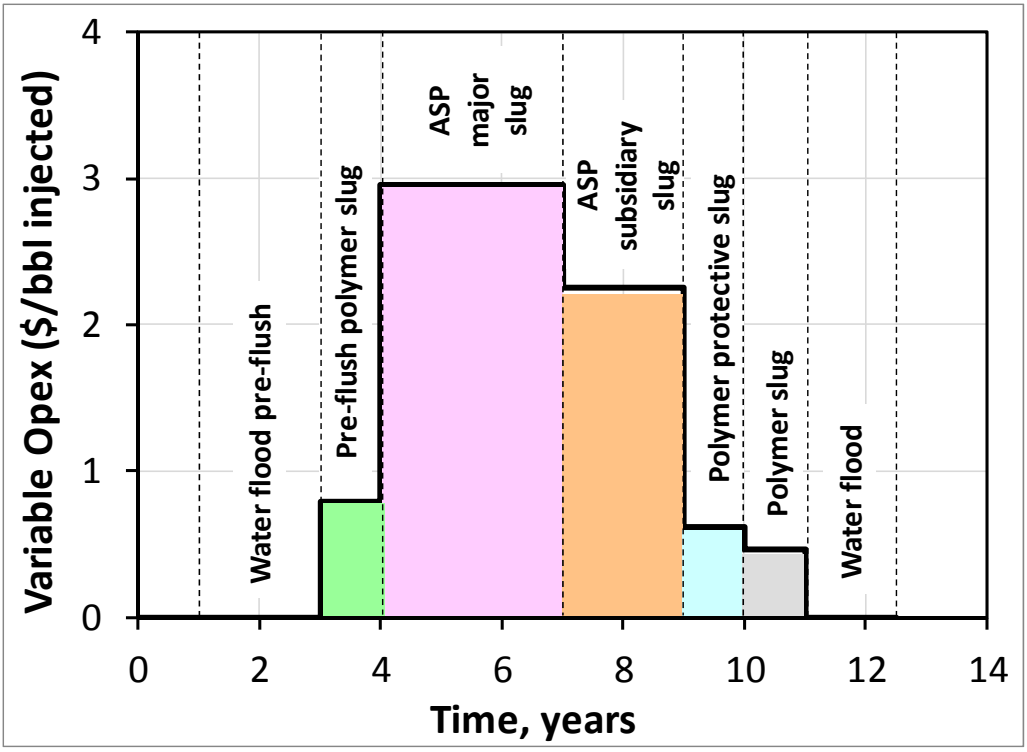

Figure 30: Variable Opex on a per barrel basis used for each of the flooding periods in the reservoir-to-market benchmark model.

Earnings before Taxes, Loss Carry Forward, and Taxable Income

The earnings before taxes and loss carry forward numbers calculated by the reservoir-to-market model are in Figure 31, which also includes a curve of their summation. The net earnings before tax curve represents the value calculated for a given month; it is simply the revenue minus the Opex minus the depreciation for that month. The loss carry forward represents the cumulative losses during the project that have not been offset by positive net revenue. Carrying losses forward can offset some or all of the income for a particular time period at which income taxes need not be paid, as income tax is paid only on net gains, not net loses. The cumulative net earnings before taxes and the

loss carry forward are useful in determining taxable income. This plot is negative where the large Capex items are incurred at the beginning of the project, and turn positive shortly after when revenues from oil production are exceeding costs.

Figure 32 shows a similar plot, where a plot of taxable income is substituted from net earnings before tax. This shows that the net earnings before tax plus loss carry forward curve follows the loss carry forward and taxable income curves when the plot is negative and positive, respectively.

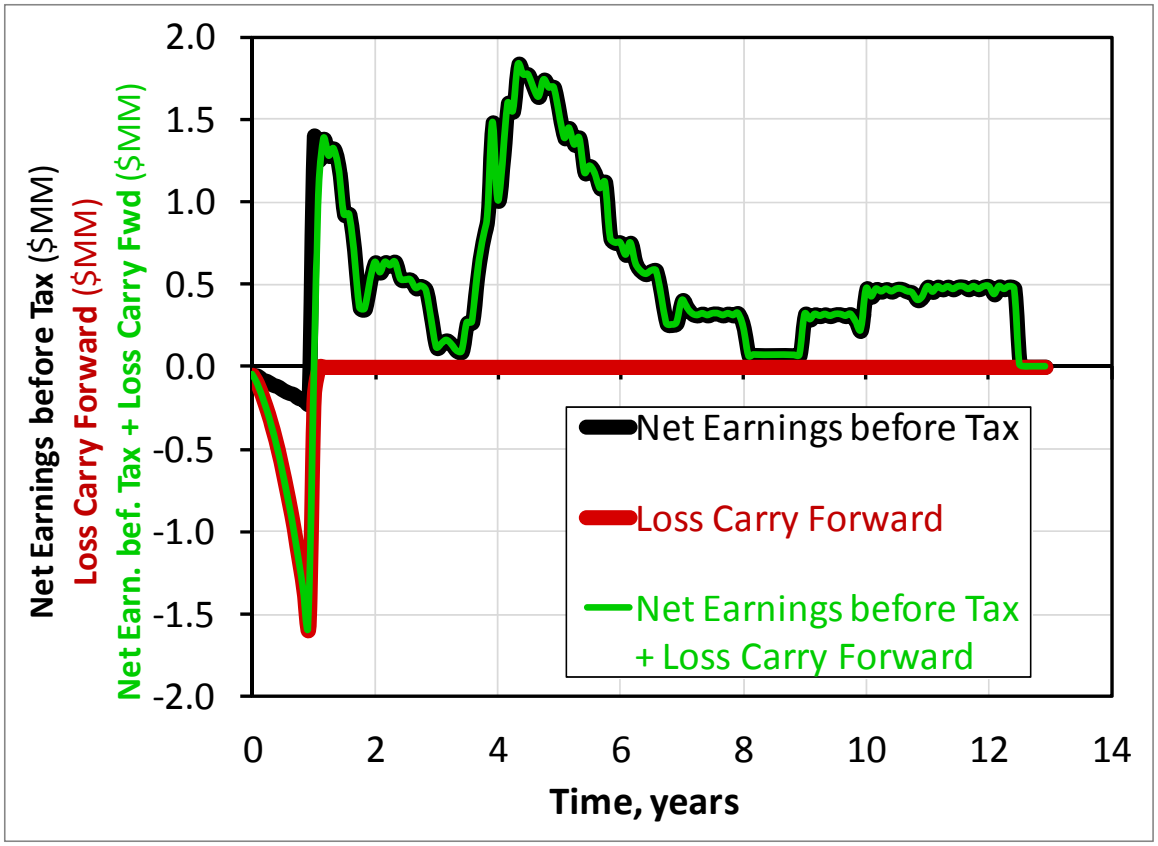

Figure 31: Net earnings before tax, loss carry forward, and their summation results generated by the reservoir-to-market benchmark model.

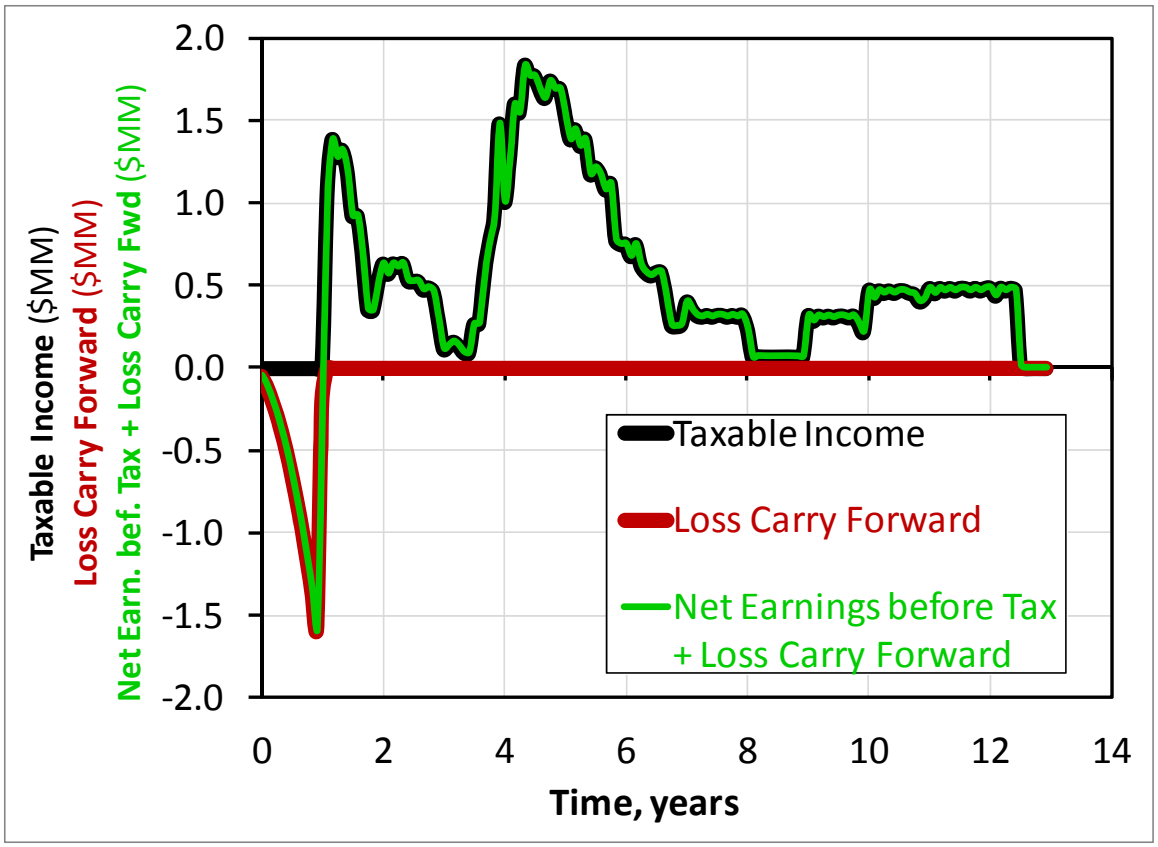

Figure 32: Taxable income, loss carry forward, and the summation of net earnings before tax plus loss carry forward generated by the reservoir-to-market benchmark model.

Taxable income, and federal and state income taxes

Figure 33 shows the taxable income taken from Figure 32, and also shows the calculated federal and state income taxes. As shown previously, taxable income only exists during the first year, between the fourth and sixth years, and around year 12, even though there may have been positive net earnings at other times. The federal and state income tax rates were 35 and 5%, respectively, and therefore the respective tax curves are essentially scaled down versions of the taxable income curve. The income taxes will ultimately be a component that subtracts out from revenue to give after tax cash flow. As

discussed previously, a 35% federal income tax rate was used because it is the standard federal corporate income tax rate for the US. Additionally, a 5% state corporate income tax rate was used because it is a reasonable and representative approximation of the income tax that varies from state to state.

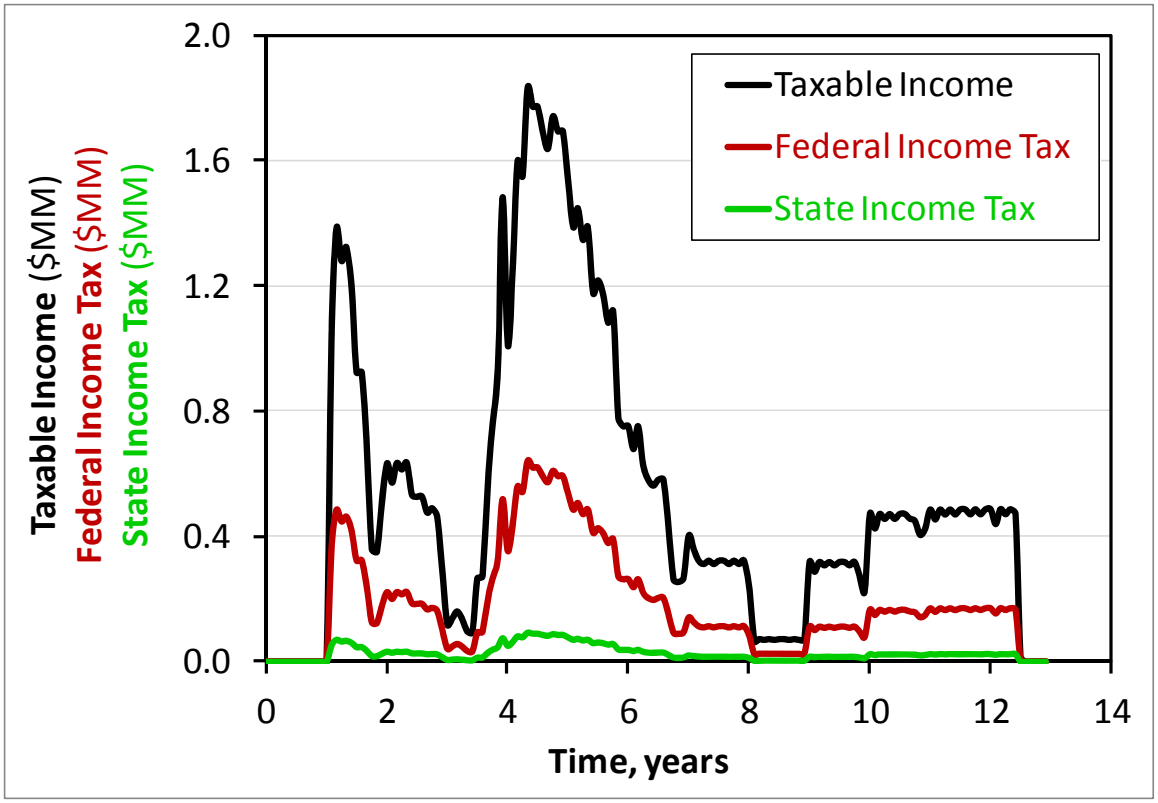

Figure 33: Taxable income and federal and state income tax results from the reservoir-to-market benchmark model (using a standard US federal tax rate and approximate state rate).

Cash Flow

The monthly cash flows and NPV of cumulative discounted cash flow (using 5% discount rate) over the project life are in Figure 34. The monthly cash flow after tax is the revenue minus royalty and severance minus Capex and Opex minus income tax for a given month.

After the initial investment period during the first year, the monthly cash flows are almost always positive throughout the life of the project. The negative cash flow spike at the end of the project life is the abandonment cost of nearly $2.5 million. The NPV of the cumulative discounted cash flow curve is negative for about one-third of the project, becoming positive just after year four (which is the payback period). Its shape is also similar to the simplified curve shown in Figure 15. At the beginning of the project, the initial investment causes an enormous outflow of cash, reaching a low point around negative $25 million before climbing again from positive cash flows during the first year. The cumulative discounted cash flow continues to become less negative, and turns positive around the ninth year. The abandonment costs cause the cumulative discounted cash flow curve to drop at the end of the project; however, the NPV of the abandonment cost is roughly about 55 to 60% of the actual $2.5 million cost given that it occurs about 12 years in the future. Therefore, an abandonment rate of 10% of Capex when undiscounted would be around 5.5 to 6% when discounted over 13 years, thus making it smaller.

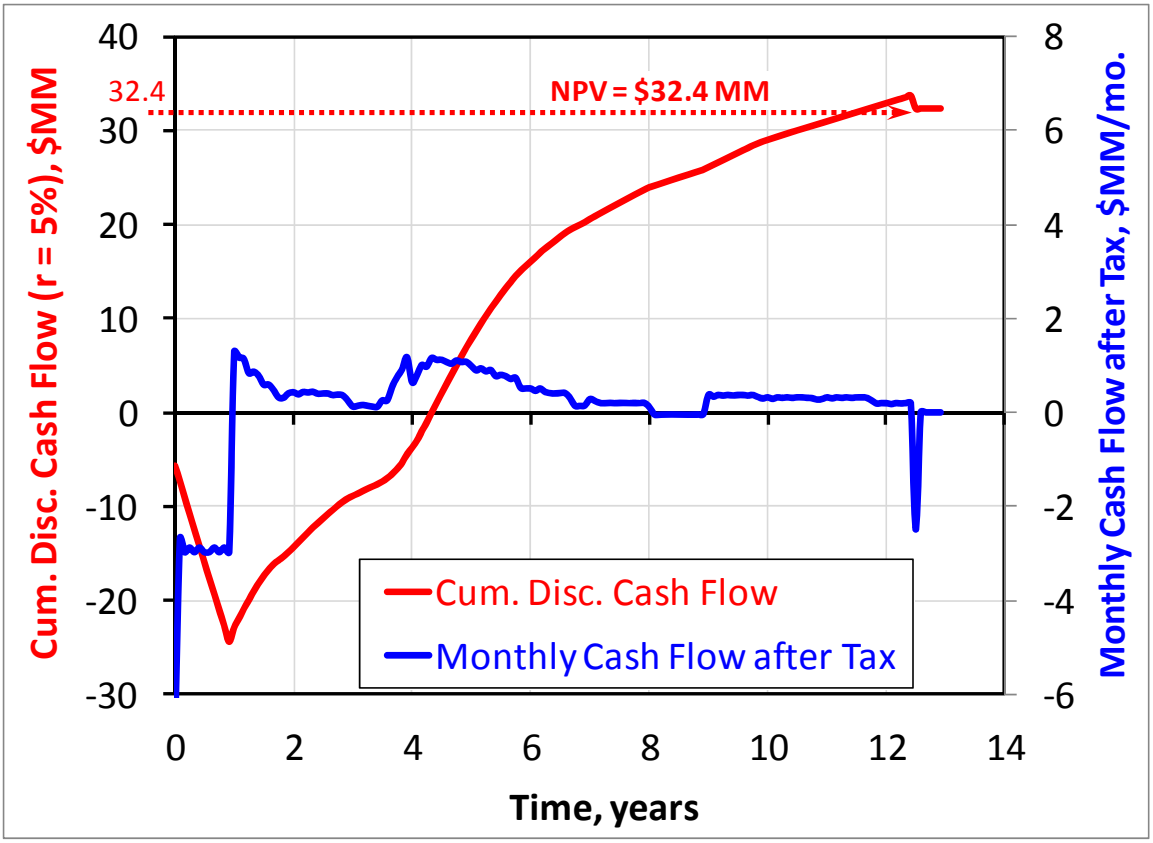

Figure 34: Cumulative discounted cash flow and monthly cash flow results generated by the reservoir-to-market benchmark model.

Economic Metrics (NPV, IRR, UTC, VIR, and Payback Period) and other results

Although the previous subsections showed an extensive analysis of the project economics, other simple economic metrics can provide quick, informative information for determining project feasibility. The main economic metrics discussed previously include: NPV, IRR, UTC, VIR, and payback period. Table 10 lists these economic metrics and other results for the reservoir-to-market benchmark model. The NPV calculated at a 5% discount rate was $32.4 million, indicating a positive NPV. The IRR, however, was actually 30.5%, meaning that if a discount rate less than 30.5% was used,

the NPV would be positive. Figure 35 shows a figure of NPV versus discount rate, demonstrating where the IRR is calculated. The project NPV becomes negative with discount rates beyond 30.5%. If one had the choice between investing in a high-risk project giving this type of return versus an alternative low risk debt instrument (e.g. 10-year government bond), the high risk project would generally be taken because of the higher to reward the risk.

The undiscounted UTC was calculated to be $42.79/STB of oil, which is reasonable given the price of oil at $100/STB of oil. This is the undiscounted UTC. The discounted UTC using a 5% discount rate is about $45.76 per discounted stock tank barrel. The VIR was calculated to be 2.03, which is greater than one, and therefore the project NPV is greater than the initial investment. The payback period was 4.3 years. Other results in Table 10 shows total oil produced of 1.97 MMSTB. Additionally, the maximum cash out during the project was -$24.4 million, total royalty (undiscounted) was $19.1 million, total severance (undiscounted) was $9.5 million, total federal income tax was $29.3 million, and total state income tax was $4.2 million. Therefore, the combined undiscounted income taxes were $33.5 million, which was $25.6 million when discounted over the life of the project using a 5% discount rate.

Table 10: Economic metrics and other results generated from the reservoir-to-market benchmark model, which is a multi-patterned pilot.

ITEM	VALUE
Economic Metrics	
Net Present Value (NPV) at 5% discount rate, $MM	32.4
Internal Rate of Return (IRR), %	30.5%
Unit technical cost (UTC) undiscounted, $/bbl oil	42.79
Value to Investment Ratio, VIR	2.03
Payback Period, years	4.3
Other Results, undiscounted	
Total Oil Produced, MMbbl	1.97
Maximum Cash Out, $MM	-24.4
Total Royalties, $MM	19.1
Total Severance, $MM	9.5
Total Federal Income Tax, $MM	29.3
Total State Income Tax, $MM	4.2

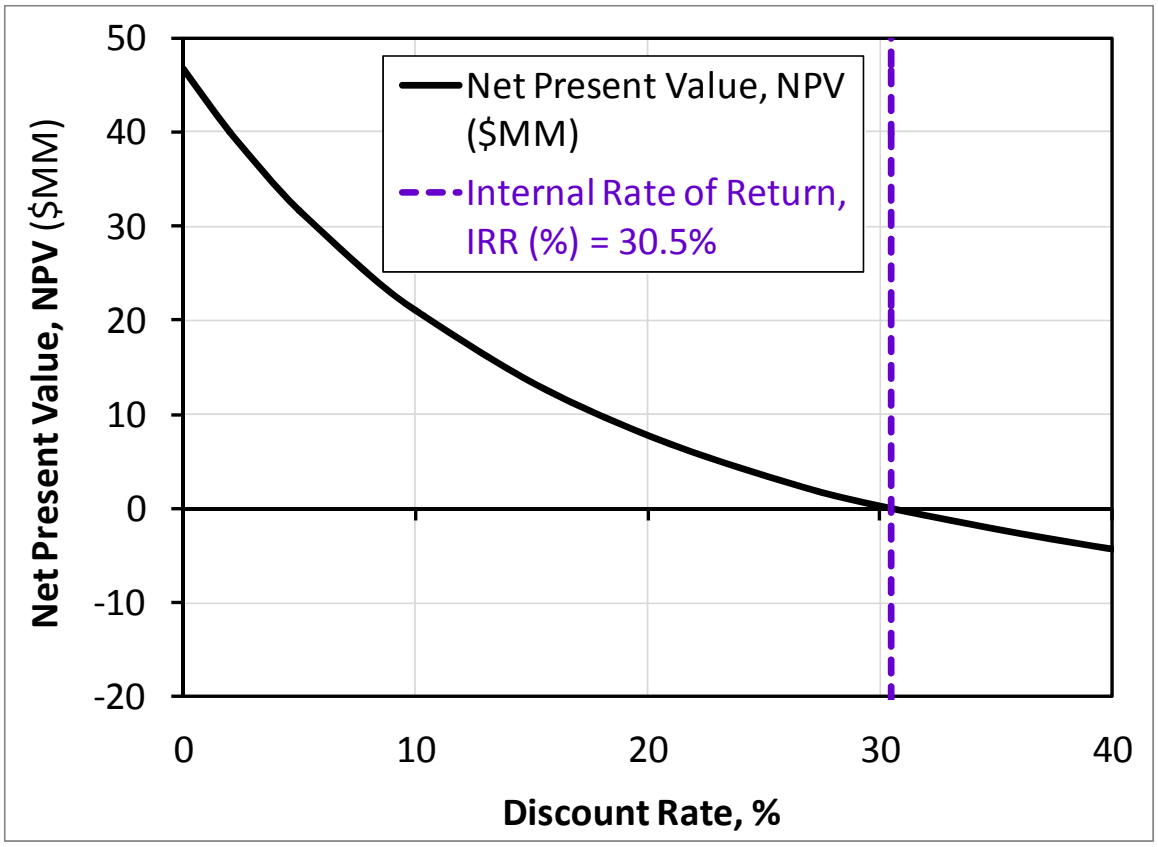

Figure 35: NPV versus discount rate with IRR displayed calculated from the reservoir-to-market benchmark model results.

Total costs and cost per barrel oil produced

Table 11 shows input parameter item cost using discount rates of 0% and 5%. Similarly, shows input parameter category costs using 0% and 5% discount rates as well. The total costs over the life of the project are about $84 million and $68 million for 0% and 5% discount rates, respectively. Although cost items with more Opex than Capex may not necessarily be discounted more simply because Opex occurs throughout the project life, as Capex is depreciated over the project life as well. Table 12 shows the undiscounted and discounted cost breakdown of input parameters and categories on a

$/bbl oil produced basis. The discounted costs are normalized to discounted barrels of oil produced. Chemical and treated water inputs account for almost 40% of costs, which is similar for facilities as well. Ansel Adams

Table 11: Cost breakdown of input parameters and categories on a total cost basis, both undiscounted and discounted.

ITEM	COST, $MM	
	Undiscount.	5% disc. rate
By Input Parameter		
Surfactant	12.22	9.12
Chemical mixing/injection facility	12.19	10.92
Polymer	10.85	7.99
Alkali	9.04	6.62
Produced fluids processing (Opex)	9.02	6.85
Central production processing facility (Capex)	8.00	7.82
Wells (Opex)	7.18	5.24
Source water treatment facility	6.77	5.97
Existing well tubing (Capex)	3.90	3.90
Water treatment	3.69	2.67
Produced fluids test facility	1.35	1.23
Well pad (Opex)	0.09	0.07
TOTAL	**84.29**	**68.40**
By Category		
Facilities	37.32	32.79
Chem/Inj. Water	35.80	26.40
Wells	11.17	9.21
TOTAL	**84.29**	**68.40**

Table 12: Cost breakdown of input parameters and categories on a cost per barrel of oil produced basis, both undiscounted and discounted.

ITEM	COST, $/bbl oil	
	Undiscount.	5% disc. rate
By Input Parameter		
Surfactant	6.20	6.10
Chemical mixing/injection facility	6.19	7.31
Polymer	5.51	5.34
Alkali	4.59	4.43
Produced fluids processing (Opex)	4.58	4.58
Central production processing facility (Capex)	4.06	5.23
Wells (Opex)	3.64	3.51
Source water treatment facility	3.44	3.99
Existing well tubing (Capex)	1.98	2.61
Water treatment	1.87	1.79
Produced fluids test facility	0.68	0.82
Well pad (Opex)	0.05	0.05
TOTAL	**42.79**	**45.76**
By Category		
Facilities	18.95	21.94
Chem/Inj. Water	18.17	17.66
Wells	5.67	6.16
TOTAL	**42.79**	**45.76**

OVERALL OPPORTUNITY VALUATION AND FINAL DEVELOPMENT DECISION

The various economic metrics calculated from the reservoir-to-market model can be used for opportunity valuation and final development decision of a chemical EOR project. Table 10 shows the calculated economic metrics from initially running a base case model to be relatively favorable, with a positive NPV (at 5% discount rate) of $32.4

million, IRR of 30.5%, undiscounted UTC of 42.79 $/STB, and VIR greater than one at 2.03.

Additional tools in the reservoir-to-market model can be used to identify, understand, and improve unfavorable economic parameters. Sensitivity and scenario analysis may help identify what changes need to happen to cause the greatest economic improvement, which helps with model simplification.

Regardless of the favorable or unfavorable economic output from the reservoir-to-market model generated early in the project lifecycle, much uncertainty likely exists. Further inexpensive laboratory testing and simulation may help reduce uncertainty for parameter distribution inputs and help in confidently justifying a pilot project. Additionally, different development scenarios can be compared using decision tree analysis and model generated economic metrics in order to select most feasible project. However, when a final investment decision is ultimately made for a project, it is important to have a single development scenario of interest with favorable economic metrics generated from a production forecasting and economic analysis tool such as a reservoir-to-market model.

SUMMARY AND CONCLUSIONS

A reservoir-to-market benchmark model was successfully developed for an onshore chemical EOR multi-patterned pilot. Overall, the various economic metrics generated from the reservoir-to-market model demonstrated a method that can be used for opportunity valuation of a chemical EOR project. Input parameters for well performance, chemical inputs, and injection scheduling were obtained from an ASP flood analogue, and reasonable cost and economic assumptions were used. Economic metrics generated from benchmark model output showed favorable results for the project valuation. This

benchmark model forms the groundwork for additional model tuning, simplification, and upscaling. In the next chapters, a global sensitivity analysis will identify specific inputs that have the least and greatest impact on project economics. Global sensitivity analysis can also be useful in model simplification by discarding input parameter distributions that show a negligible sensitivity. Furthermore, discretization techniques are used to simplify the number of input parameters represented by distributions, making the model more efficient and accurate. Discretization is used to assess different development scenarios using decision tree analysis. The model will then be upscaled.

Several important conclusions were made when developing the reservoir-to-market benchmark model. The overall economics of the multi-patterned pilot project were favorable. The NPV was $32.4 million using a 5% discount rate, and the IRR was 30.5%. Furthermore, the project paid back relatively quickly at 4.3 years. Even though the maximum cash out was -$24.4 million after the first year, due to large Capex items, these costs were recovered quickly. Because the project was a pilot, it was abandoned after a set period of time (11.5 years), and did not reach an economic limit where monthly cash flow turns negative.

The well layout contained nearly twice as many injector wells as producer wells, which affected the chemical slug pore volumes injected. Both the major and minor ASP slugs collectively accounted for 0.95 pore volumes injected, which is very high for a chemical slug. However, a pilot project of this nature where injector wells surround a small number of producer wells expects excess chemicals to be injected. When the model is upscaled later, injector to producer ratio drops by almost 40%, which decreases the pore volumes of chemical slug required. Chemical costs are high, and pilot projects are generally expected to have a lower rate of return than commercial scale floods.

Chemical costs accounted for more than 40% of the total undiscounted costs and costs per barrel of produced oil. Facilities also accounted for more than 40% of costs, while wells costs accounted for almost 15%. Surfactant was the highest cost item, accounting for about $6.20 per barrel of oil produced. Polymer and alkali were the 3rd and 4th highest costs at $5.51 and $4.59 per barrel oil, respectively. This shows how significant chemical costs are in chemical EOR, and the importance of designing the flood with as little chemical as possible to achieve the desired benefit. Other high cost were costs associated with facilities Capex and Opex. The chemical mixing/injection facility, produced fluids processing, and the central production processing facility accounted for $6.19, 4.58, 4.06 per barrel oil, respectively. The overall undiscounted UTC for the project was $42.79 per barrel oil produced.

The flooding slug sequence used in the benchmark model was designed after the Daqing multi-patterned pilot project. The pilot contained five different polymer and ASP flooding periods, as well as waterflood periods before and after chemical flooding. Laboratory experiments generally contain only two chemical flood periods, a surfactant slug and a polymer drive. However, for the sake of keeping the analog data as representative of the actual pilot as possible, all five chemical flooding periods plus two waterflood periods were used in the model. As a side note, the second polymer slug prior to waterflooding in the Daqing analog did step down the polymer concentration by almost half, which can have an economic benefit due to savings in polymer costs.

CHAPTER 7: CAPTURING UNCERTAINTY AND SENSITIVITY IN DEVELOPMENT SCENARIOS AND DECISION-TREE ANALYSIS

INTRODUCTION

A field development opportunity will always have uncertainty associated with it, as well as several alternative possible development scenarios. Each of the many input parameters making up a reservoir-to-market model have uncertainty associated with them, which results in uncertainty in the output. Uncertainty is commonly captured mathematically by defining input parameters by probability distributions, where the expected value and range is obtained from historical data and/or experience. Sensitivity analysis is a systematic method for mathematically describing how input parameter changes within their defined distribution affects the outcome.

A development opportunity also can have many potential development scenarios, each of which may have different input parameters and/or uncertainties given availability of information. Decision-tree analysis methods can be used to determine the economically optimal development given the various input and uncertainty. This chapter will detail the process of capturing uncertainty, performing sensitivity analysis and discretization of reservoir-to-market model input parameters for model simplification and efficiency, and using models for decision-tree analysis to assess potential development scenarios.

UNCERTAINTY CHARACTERIZATION AND MODEL SIMPLIFICATION

A well constructed reservoir-to-market model should sufficiently capture the uncertainty of the many input parameters, defined either by discrete or continuous ranges of values to represent uncertainty. Several methods are presented in this section for capturing uncertainty, depending on what prior data and experience is known. After input

parameters are represented, model simplification strategies can be applied for a simpler, more efficient model.

First, for particular input parameters where their uncertainty contributes negligibly and/or minimally to the output uncertainty, they can be fixed at an expected value and their uncertainty range subsequently discarded with minimal impact to the model. A global sensitivity analysis is the preferred method to accomplish this, which is presented in this section.

Second, once the number of uncertainty ranges for different input parameters has been reduced, parameters that still contain uncertainty can be simplified through discretization. Discretization was also explored, and shown to simplify and add efficiency to a model without necessarily increasing error.

CHARACTERIZING UNCERTAINTY

Uncertainty is commonly captured statistically by defining a range of discrete or continuous values, each with associated probabilities or probability distribution, respectively, to a parameter. Input parameters are initially defined using a variety of distribution functions, with the more standard ones including: normal, log normal, truncated normal, truncated log normal, triangular, and uniform.

When identifying the uncertainty of various input parameters, there are advantages and disadvantages in using deterministic versus probabilistic methods:

- Deterministic data is simplistic and easy to understand and communicate, but may be underrepresented and difficult to assign a probability of occurrence for each value.
- Probabilistic data is a nearly all-inclusive data range, can include a lot of sample data, and easily defines frequency of occurrence; however, it is

difficult to communicate, augment data to a pre-defined distribution, and capture full uncertainty ranges in large simulation models.

For the use of statistical distributions, input parameters have an expected value (e.g. mean in normal distribution) and range, which is obtained/defined based on using fundamental principles/physics/mechanics, historical or analogue data (objective), and/or expertise (subjective). Early in the life of a project, the distribution ranges are usually larger to represent more uncertainty, and generally narrow as more information is gathered throughout the project.

The benchmark model output generated previously used all the expected values for input parameters, which are generally the values with the highest probability of occurrence in a distribution. Moreover, simply using the most expected value does not consider the range of possible outcomes. Acquiring additional data can help reduce the uncertainty, which narrows a distribution range or eliminates possible discrete values, and sensitivity analysis can render particular uncertainty distributions as non-influential.

Uncertainty analysis is a systematic process used to identify and define the ranges and/or distributions of all input data. The first step is usually to identify all the parameters that could influence project development, and identify their possible ranges and/or distributions. For probabilistic values, generating probability density functions for the parameters is required. An optional, but useful second step would be to categorize and/or classify input parameters according to the degree (say low, medium, or high) to which they can influence more general outcomes (say well performance, facilities constraints, etc.). Categorizing is often useful in understanding individual parameters, and categories can sometimes provide a simpler understanding of how the overall project value is influenced.

A more systematic method is a global sensitivity analysis, which ultimately provides quantifiable classification on how each input parameter affects output, either acting alone or in conjunction with other inputs.

Methods of quantitatively representing uncertainty

The most common way of quantitatively representing uncertainty for a particular input parameter is through a distribution of values. There are many types of distributions; however, the more standard ones include normal, lognormal, triangular, and uniform. Distributions can be either discrete or continuous. Discrete distributions are a finite collection of values with assigned probabilities to those values. Continuous distributions have an infinite set of values with a probability distribution function assigned to the range or ranges at which the values cover. For this particular study, continuous and non-truncated normal distributions were used to define all uncertain input parameters; however, a brief description truncated distributions is given below because several studies have given relevance to them for oil and gas projects.

In the oil and gas industry, input parameters are commonly assigned a normal or lognormal distribution; however, truncating these distributions can be important for several reasons. Truncated distributions are distributions that have a restricted domain or range that can be based on any of the standard families of distributions mentioned previously (normal, lognormal, triangular, etc.). Truncating the distribution of certain parameters can be practical when data values outside of that range have no practical value. For example, the theoretical range of a normal distribution extends for an infinite number of standard deviations from the mean.

In probabilistic modeling, even though the chance is minute of selecting a value from a distribution, say four standard deviations from the mean, the possibility still exists.

For example, say chemical mixing and injection facility Capex for the project (based on historical data, etc.) generally follows a normal distribution, with expected value of $8 million and standard deviation of $3 million. A value of three standard deviations higher at $17 million would likely be an impractical assumption as the project either would not go through or other vendors would tender lower bids. Furthermore, a value three standard deviations lower at -$1 million clearly is not sensible (a lognormal distribution could be used to avoid negative values, but distributions may not be logarithmic).

Another instance where truncated distributions may be useful is when distributions are derived from data points containing extreme outlier data that is clearly erroneous, impractical, and/or non-sensical. A distribution may then be truncated at particular endpoints in order to represent a practical range of values.

Truncated distributions can be of practical importance in oil and gas project applications. Several studies discuss the use and application of truncated distributions. For example, Thanh (2002) uses truncated distributions for parameters in reserves estimation to eliminate non-sensical and/or prevent sampling outside a sensible data range. Gair (2003) assesses and truncates sample data for reserves estimates that clearly fits a normal distribution (as opposed to log-normal), and truncates values outside of a reasonable range. Guttormson et al. (1972) discusses truncated symmetrical distributions in their work on gas plant design.

SENSITIVITY ANALYSIS FRAMEWORK

Sensitivity analysis determines the affects of each input parameter uncertainty on the output uncertainty. A global sensitivity method is the preferred approach to characterize individual as well as total (individual plus interaction) effect on sensitivities for each input parameter. Furthermore, sensitivity analysis can help with model

simplification by determining which input parameter uncertainty has a negligible and/or minimal contribution on output uncertainty, and whether they can be fixed at an expected value and their uncertainty range subsequently discarded with minimal impact to the model outcome.

Theoretical Framework

The following describes the theoretical framework for analyzing sensitivity, description of Monte Carlo simulation to calculate output as a function of input uncertainty, the Sobol method as a global sensitivity method, and a sensitivity analysis application to the benchmark reservoir-to-market model with the objective of model simplification. Lawal (2007) provides a good description for this theoretical framework that can be referenced for additional detail.

Lets assume the results of a model f that is dependent on a set of k uncertain input parameters, with inputs identified generally as X. Therefore, the set of inputs will be $(X_1, X_2, \dots, X_k)$, with each input having uncertainty. The resultant model output Y will therefore be a function of these inputs that can be expressed generally as:

$$Y = f(X_1, X_2, \dots, X_k)$$

Uncertainty in X results in uncertainty in Y, and the objective of applying a sensitivity analysis to model f is simply to characterize how varying X affects Y.

The two types of effects that varying X can have on Y include: main effects and interaction effects. The main effect of a particular input X_i characterizes how Y changes independent of all other inputs $X_{\sim i}$, where $X_{\sim i}$ is simply inputs that are not X_i (Lawal, 2007). In contrast, the interaction effects of input X_i characterize how Y changes with

interaction between X_i and $X_{\sim i}$. Throughout this paper, the symbol $\sim i$ will be used to represent when a set of k input parameters all vary except for input parameter i, which can otherwise be described as $k \neq i$.

Variance theory and sensitivity is well known, and has been applied in statistics for petroleum engineers for a while; however, Lawal (2007) can be referred to for further details. The variance, V, of a particular parameter, say the output Y, is simply the expected value, E, of the squared difference between the actual output and expected output:

$$V(Y) = E\{[Y - E(Y)]^2\}$$

From this starting point, the law of total variance can be solved for, which says the variance of Y is the sum of the expected conditional variance of Y (conditional on input X) and the variance of the conditional expectation of Y:

$$V(Y) = E\big(V(Y|X)\big) + V\big(E(Y|X)\big)$$

For a given set of inputs $(X_1, X_2, \dots, X_k)$, the law of total variance can be defined for a particular input X_i as:

$$V(Y) = V\big(E(Y|X_i)\big) + E\big(V(Y|X_i)\big)$$

The first part of the equation, $V\big(E(Y|X_i)\big)$, consists of the main effects of only X_i. The second part, $E\big(V(Y|X_i)\big)$, constitutes all the other sources of variance, which include the main effects of other inputs, $X_{\sim i}$, as well as all interaction effects.

In general, the sensitivity, S, of various input parameter effects is simply the proportion of the total variance that the effect is accountable for. In order to mathematically define the different sensitivities, all the different partial variances should be described. The sensitivity of only the main effect of input X_i is the partial variance caused only by X_i (independent of $X_{\sim i}$) relative to the total variance:

$$S_i = \frac{V\big(E(Y|X_i)\big)}{V(Y)}$$

The total variance is the sum of all main effect variances, V_i, and interaction variances, whether a two variable (e.g. X_i and X_j) interaction variance, V_{ij}, or interaction variance of all variables $V_{12\dots k}$:

$$V(Y) = \sum_{i=1}^{k} V_i + \sum_{i=1}^{k} \sum_{j=i+1}^{k} V_{ij} + \cdots + V_{12\dots k}$$

The individual components of the total variance equation can be expressed mathematically as such:

$$V_i = V\big(E(Y|X_i)\big)$$

$$V_{ij} = V\left(E\big(Y|X_i, X_j\big)\right) - V_i - V_j$$

$$V_{12\dots k} = V\big(E(Y|X_1, X_2 \dots X_k)\big) - \sum_{i=1}^{k} V_i - \sum_{i=1}^{k} \sum_{j=i+1}^{k} V_{ij} - \cdots - \sum_{i=1}^{k} \sum_{j=i+1}^{k} \dots \sum_{m=i+k-1}^{k} V_{ij\dots m}$$

Using these relationships, both sides of the total variance equation can be divided by $V(Y)$ to express the different sensitivities:

$$1 = \sum_{i=1}^{k} S_i + \sum_{i=1}^{k} \sum_{j=i+1}^{k} S_{ij} + \cdots + S_{12\ldots k}$$

All the sensitivities sum to 1. As mentioned previously, S_i is the sensitivity of the main effect of input parameter X_i on Y. The total effect of X_i on sensitivity, or S_{T_i}, is the variance of expectation of Y when $X_{\sim i}$ is kept constant, which is expressed as such (Lawal, 2007):

$$S_{T_i} = S_i + \sum_{j=1}^{k} S_{ij} + \sum_{j=1}^{k} \sum_{m=2}^{k} S_{ijm} + \cdots + S_{12\ldots k} \quad , \quad j, m \neq i;\ j \neq m$$

or:

$$S_{T_i} = 1 - \frac{V\big(E(Y|X_{\sim i})\big)}{V(Y)}$$

Sampling and Sensitivity Analysis Methods

The nature of sensitivity analysis is dependent on how data is sampled from a distribution, and subsequently how this data is analyzed once sampled. Sensitivity analysis methods change (i.e. sample) different input parameters, and characterize the response this has on the output. Inputs can be defined as a discrete or continuous set of values or probability distribution.

Sampling methods of inputs can include one-at-a-time (OAT) sampling and concurrent (or simultaneous) sampling (Lawal, 2007). OAT sampling is where only one input parameter is changed while all others are held constant. Although this method is simple, only the first-order, or main, effects of the varying input parameter on the output can be analyzed. Concurrent sampling is where more than one input parameter is varied simultaneously and independently of each other, and both the main and interaction effects that varying inputs have on output and each other can be analyzed. Generally, the main effects account for the majority of sensitivity in a model; however, interaction effects are often not insignificant either.

Sensitivity analysis methods can be either local or global. A local method occurs at a fixed point (i.e. locale) in the input sample space, $\mathbf{X_O}$, and will characterize the change that varying one input parameter X_i has on Y: $\left.\frac{\partial Y}{\partial X_i}\right|_{\mathbf{X_O}}$. Essentially, this method constitutes one-dimensional movement along the X_i range within a sample space. In contrast, a global method considers every location within a sample space that is essentially multi-dimensional movement along the ranges of all inputs $(X_1, X_2, \ldots, X_k)$.

Various deterministic and stochastic analyses techniques generally reflect local and global sensitivity analysis methods. Monte Carlo analysis (frequently referred to as simply stochastic analysis) is likely the most common method for assessing every data point within a sample space. Input/output results from Monte Carlo can be used to perform a global sensitivity analysis using a number of different methods (e.g. regression-based, correlation-based, variance-based).

Monte Carlo simulation

Monte Carlo analysis is a stochastic method of calculating probabilistic outcomes given various input parameters each having a probability distribution. Input parameters

can be defined using a variety of distribution functions, with the more standard ones including: cumulative, discrete, normal, log normal, truncated normal, truncated log normal, triangular, and uniform. A Monte Carlo analysis involves randomly selecting a particular input value from each distribution, and running a simulation (e.g. reservoir-to-market model) to arrive at particular output values. Several different methods exist for sampling input distributions (e.g. random, Latin Hypercube, low-discrepancy), which will be discussed in the following subsection. The Monte Carlo simulation is generally run for a sufficient number of iterations to stabilize the output mean and minimize the variance of the means (also to be discussed), which generally enables smooth probability distributions, or cumulative distribution functions, of the output values. A Monte Carlo analysis has the advantage of calculating scenarios covering nearly an entire sample space, and therefore sufficiently capturing a defined range of uncertainty in a project. This is a clear advantage to a possibly overly simplistic deterministic approach of selecting single, expected values as inputs to arrive at only one particular output value.

Sampling methods for Monte Carlo

For Monte Carlo simulation, input parameters are characterized by probability distributions, and one value must be sampled from each distribution per iteration (i.e. simulation run). The objective of a sampling method is for quick convergence (short sampling time), and independence (samples are un-related and un-correlated to each other) (Lawal, 2007).

Random sampling is unsystematic, unordered, and arbitrary, and is the simplest of all the sampling methods. Although a sufficient number of sampling iterations should, in theory, be representative of each input parameter probability distribution, random sampling can be subject to clustering effects. Alternative sampling methods, such as

Latin Hypercube, were developed to minimize clustering effects, and more consistently represent the input probability distributions with fewer number of samples.

Latin Hypercube sampling is a stratified, or constrained, sampling method that is discussed at length by Wyss and Jorgensen (1998). For each probability distribution representing an input parameter, the range is divided into non-overlapping intervals on the basis of equal probability, and the number of intervals corresponds to the Monte Carlo iterations. One value is then randomly selected from each interval according to the interval's probability distribution. All values for each input parameter are then randomly paired, giving each iteration one input value for each parameter.

Monte Carlo iterations

The appropriate number of iterations performed in a Monte Carlo simulation has occurred when no significant change in a statistical estimator (e.g. arithmetic mean) of the response variable (e.g. cumulative discounted cash flow) with additional iterations (Lawal, 2007). Lawal (2007) discusses statistical efficiency and consistency as two criteria for determining convergence. The statistical efficiency of an estimator increases when its variance decreases as the iterations tend to infinity. Consistency is achieved when the estimator converges to an increasingly narrow range. Sufficient iterations depend on the sampling method, and the nature of the inputs parameters and model functions (linear, additive, non-linear, etc.).

The benchmark reservoir-to-market model contains most of the input parameter and model function complexity that any additional scenario model would contain. Therefore, it is representative for determining the appropriate iteration number. The benchmark model was used to run 1000 Monte Carlo simulations, and the resultant cumulative discounted cash flow NPV (using a 5% discount rate) served as a response

variable, with arithmetic mean and variance of arithmetic mean used as statistical estimators.

Figure 36 plots the mean and mean variance versus 1000 Monte Carlo simulations. The mean has sufficiently stabilized at about 1000 iterations, which is also supported by a near-zero variance. Therefore, 1000 iterations will be used for Monte Carlo simulations in this study.

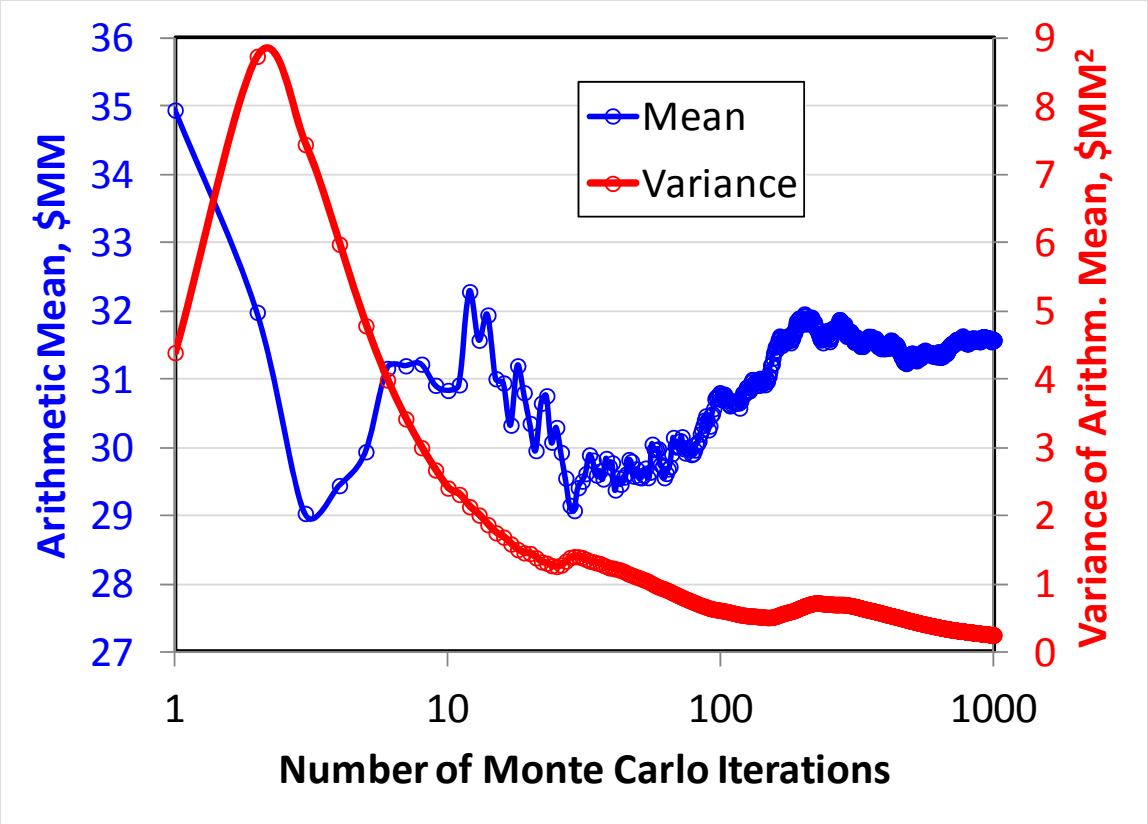

Figure 36: Arithmetic mean and arithmetic mean variance of NPV (using 5% discount rate) for cumulative undiscounted cash flow versus Monte Carlo iterations.

Statistical Analysis

The Monte Carlo method provides a means to systematically sample input data and subsequently obtain model output. However, once this input/output data has been obtained, it must be analyzed further to, in this case, determine input parameter sensitivities and ultimately to simplify the model. Three commonly used methods are: regression based methods, rank based regression and correlation methods, and variance based methods. Variance based methods can analyze the main and total sensitivity indices of input parameters based on resultant input/output from Monte Carlo iterations. Much of the theoretical framework behind variance based methods in general was described previously, and the following subsection will explore the Sobol method as a global, variance based method for sensitivity analysis.

Sobol Method

The Sobol Method is a global, variance-based method for sensitivity analysis, which assesses Monte Carlo variables for both main and total sensitivity. Lawal (2007) details the Sobol algorithm used to calculate these sensitivities, which is described here.

The first step of the Sobol Method is to generate two sample matrices, M and M', consisting of input parameters X and X', respectively, each with k input parameters for n iterations (e.g. 1000 as discussed previously). These matrices are arranged as such:

$$M = \begin{Bmatrix} X_{11} & X_{21} & \cdots & X_{j1} & \cdots & X_{k1} \\ X_{12} & X_{22} & \cdots & X_{j2} & \cdots & X_{k2} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ X_{1n} & X_{2n} & \cdots & X_{jn} & \cdots & X_{kn} \end{Bmatrix}$$

$$M' = \begin{Bmatrix} X'_{11} & X'_{21} & \cdots & X'_{j1} & \cdots & X'_{k1} \\ X'_{12} & X'_{22} & \cdots & X'_{j2} & \cdots & X'_{k2} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ X'_{1n} & X'_{2n} & \cdots & X'_{jn} & \cdots & X'_{kn} \end{Bmatrix}$$

The sample mean, μ_Y, of the model outputs generated from the matrix inputs can be calculated for each sample set. For M, the model output, Y_M, and sample mean, μ_M, are calculated as such:

$$Y_{M,i} = f\left(X_{M,i1}, X_{M,i2}, \dots, X_{M,ik}\right)$$

$$\mu_Y = E(Y) \cong \mu_{Y_M} = \frac{1}{n}\sum_{i=1}^{n} Y_{M,i}$$

The population mean, μ_Y^2, is then calculated using both sample sets as such:

$$\mu_Y^2 = E(Y)^2 \cong \frac{1}{n}\sum_{i=1}^{n} Y_{M,i} Y_{M',i}$$

Both the sample and population means estimate the mean; however, the sample mean is better suited for total sensitivity and population mean for first-order sensitivity (Salteli et al., 2000). The sample variance can be calculated using either M or M'; the case below uses M:

$$V_Y \cong V_{Y_M} = \frac{1}{n-1}\sum_{i=1}^{n}\left(Y_{M,i}^2 - \mu_Y^2\right)$$

The next step is to calculate the partial variances of all k input parameters, which highlights the Sobol method. The partial variance of the j^{th} input parameter is calculated as such:

$$U_j = \frac{1}{n}\sum_{i=1}^{n} f\left(X_{M,i1}, X_{M,i2}, \dots, X_{M,ij}, \dots, X_{M,ik}\right) f\left(X_{M',i1}, X_{M',i2}, \dots, X_{M,ij}, \dots, X_{M',ik}\right)$$

The first-order sensitivity of the j^{th} input parameter is then calculated as:

$$S_j = \frac{U_j - \mu_Y^2}{V_Y}$$

where the numerator, $U_j - \mu_Y^2$, is essentially the variance of the conditional expectation of Y with respect to X_j, $V\left(E\left(Y|X_j\right)\right)$, which is the main effects of X_j.

The total sensitivity can be calculated for each X_j by adjusting the partial variance calculation as such:

$$U_{-j} = \frac{1}{n}\sum_{i=1}^{n} f\left(X_{M,i1}, X_{M,i2}, \dots, X_{M,ij}, \dots, X_{M,ik}\right) f\left(X_{M,i1}, X_{M,i2}, \dots, X_{M',ij}, \dots, X_{M,ik}\right)$$

The total sensitivity index of the j^{th} input parameter is then calculated as:

$$S_{T_j} = 1 - \frac{U_{-j} - \mu_Y^2}{V_Y}$$

Sensitivity importance for model tuning and simplification

One of the key objectives in calculating sensitivity in this study is for model simplification. This is achieved by using the main $\left(S_j\right)$ and total sensitivity index $\left(S_{T_j}\right)$. Eliminating input parameter distributions (i.e. fix at expected values) for parameters that

have a negligible contribution to the overall sensitivity of the model can save on Monte Carlo computation time, focuses analysis on relevant parameters, and can make determining input parameter correlations easier. For parameters that contribute the largest sensitivity, reducing their uncertainty and narrowing their probability distribution (i.e. around an expected value) by gathering additional data would likely have the greatest impact on reducing overall model uncertainty.

The total sensitivity index, S_{T_j}, is the sum of the main and interaction effects of the j^{th} input parameter, and its magnitude will determine whether a parameter's uncertainty is important or not. To begin model simplification, one could eliminate the distribution of parameters with S_{T_j}below particular values, say 0.01, 0.05, 0.1, etc.

To test whether a S_{T_j}cutoff has oversimplified the model, output distributions could be compared between each cutoff. To determine if interactions and/or correlations exist between input parameters, the main effect, S_j, must be subtracted from S_{T_j} for each parameter, which indicates the magnitude of interactions between X_j and other variables. Parameters with significant interaction effects can then be assessed for correlations with other input parameters, which can ultimately be defined with correlation coefficients in the Monte Carlo model.

SENSITIVITY ANALYSIS APPLICATION

The reservoir-to-market benchmark model developed in this work captures the key parameters and processes for a chemical EOR pilot; however, only mean, or expected, parameter values were used to test and validate the model. To represent uncertainty, parameters are inputted as distributions rather than single values. However, particularly in the case of Monte Carlo simulation, representing all parameters with

distributions can be computationally intensive and redundant if some parameter distributions have little to no effect on the distribution of the model output.

Application of sensitivity analysis, particularly a global (e.g. Sobol) method, can determine which parameter distributions affect the model output distribution, and ultimately help omit certain input distributions for computational simplicity.

Identifying ranges of uncertainty of input parameters and Sobol analysis

In the reservoir-to-market benchmark model, a total of 11 input parameters were defined by probability distributions and used in the sensitivity analysis. For the purpose of model simplification, all parameters were defined by normal distributions with a mean value being the same as the expected value used previously, and standard deviation of 10% of the mean value.

Table 13 lists these input parameters and distribution values. The parameters include Capex, Opex, and materials costs, and consist of two well, five facilities, and four materials (i.e. chemicals and treated water) parameters. Other input parameters exist; however, they are directly tied to one of these 11 input parameters. For example, an annual fixed Opex of 3% Capex is used for the source water treatment facility, and its distribution is indirectly captured by varying the Capex value in the sensitivity analysis. Well pad Opex was omitted because of its very small cost.

Table 13: Input parameters and values (mean, standard deviation) defining their normal distribution.

ITEM	VALUE	
	Mean	Stand. Dev.
Well		
Existing well tubing Capex, $MM	0.15	0.015
Well Opex, $k/yr/well	24	2.4
Facilities		
Source water treatment facility, $MM (Capex)	4	0.4
Chemical mixing/injection facility, $MM (Capex)	8	0.8
Produced fluids test facility, $MM (Capex)	1	0.1
Central production processing facility, $MM (Capex)	8	0.8
Produced fluids processing, $/bbl (Opex)	0.5	0.05
Chemicals, treated water		
Alkali, $/lb	0.22	0.022
Surfactant, $/lb	1.85	0.185
Polymer, $/lb	1.20	0.120
Water treatment, $/bbl	0.2	0.02

Using the Sobol method described previously, two sample matrices were generated using 1000 Monte Carlo simulations for each of the 11 input parameters listed in Table 13. The sample mean of model outputs, $E(Y)$, population mean of outputs, $E(Y)^2$, and sample variance, $V(Y)$, are shown in Table 14, and are used in the Sobol calculations. Table 15 shows the partial variance calculations, U_i, $U_{\sim i}$, and $V\big(E(Y|X_i)\big)$, used in the Sobol analysis, as well as the sensitivity outputs, S_i, S_{T_i}, and $S_{T_i} - S_i$, for each input parameter.

Table 14: Calculated Sobol parameters from the global sensitivity analysis.

ITEM	VALUE
Sobol Input/Calculated Values	
Sample size, n	1000
Input parameters, k	11
Sample mean of model outputs, E(Y) ($MM)	31.57
Population mean of outputs, $E(Y)^2$ ($MM^2)	1004.34
Sample variance, V(Y) ($MM^2)	41.19

Table 15: Calculated sensitivity values for each input parameter using the Sobol method in the global sensitivity analysis.

ITEM	SOBOL ANALYSIS VALUES					
	U_i	$U_{\sim i}$	$V(E(Y\|X_i))$	S_i	S_{TI}	$S_{TI} - S_i$
Well						
Existing well tubing Capex, $MM	1006.687	1043.172	2.351	0.057	0.057	0
Well Opex, $k/yr/well	1007.497	1042.362	3.161	0.077	0.077	0
Facilities						
Source water treat. facility, $MM (Capex)	1007.935	1041.924	3.599	0.087	0.087	0
Chemical mixing/inj. facility, $MM (Capex)	1010.917	1038.942	6.581	0.160	0.160	0
Produced fluids test facility, $MM (Capex)	1005.078	1044.781	0.741	0.018	0.018	0
Central prod. process. facility, $MM (Capex)	1009.051	1040.807	4.715	0.114	0.114	0
Produced fluids processing, $/bbl (Opex)	1008.464	1041.395	4.127	0.100	0.100	0
Chemicals, treated water						
Alkali	1008.327	1041.531	3.991	0.097	0.097	0
Surfactant	1009.832	1040.027	5.496	0.133	0.133	0
Polymer	1009.150	1040.709	4.814	0.117	0.117	0
Water treatment	1005.947	1043.912	1.611	0.039	0.039	0

In Table 15, the values of U_i and $U_{\sim i}$ are pretty similar, which indicates that the variation the parameters have on the outcome overall is somewhat small. One possible explanation is that the input parameter distributions were quite narrow, with the standard deviations only being 10% of the expected mean value for each distribution. However,

when oil price is incorporated in the sensitivity analysis, the results are much different, as shown in Table 18 and Figure 41. These results will be discussed later.

As discussed previously, S_i, S_{T_i}, and $S_{T_i} - S_i$ are the first-order sensitivity index, total sensitivity index, and interaction effects of input parameter i, respectively. Total sensitivity index, S_{T_i}, values can be used to screen out input parameter distributions as redundant. In other words, input parameters that show little to no sensitivity can be fixed at their expected values to simplify the model. For example, if only the six most sensitive parameters distributions were going to be kept as a first-pass screening, any input parameter with a total sensitivity value higher than the alkali value of 0.097 would be used. This would enable five of the eleven input parameters to be fixed at their expected values.

The interaction effects $\left(S_{T_i} - S_i\right)$ determine the co-effects of two or more parameters (i.e. higher order effects) on sensitivity. In other words, an interaction exists when the change in model output with respect to a particular input parameter, i, depends on a third variable, $\sim i$ (Lawal, 2007). If input parameters have large interaction effects, the probabilistic model may be improved and/or simplified by relating parameters with correlation coefficients.

Lawal (2007) describes that some models with multiple input parameters can have no interaction effects if the model is additive. For an additive model where output Y is dependent on input X, Y can have a symmetric or normal probability distribution with constant variance (i.e. variance is homoscedastic) regardless of the mean of X_i (Lawal, 2007). The probability distribution of Y will differ only by a shift depending on the X_i values (Lawal, 2007). Alternatively, if a model is non-additive, then the variance of Y is a function of the mean of X_i (i.e. variance is heteroscedastic) (Lawal, 2007).

In this sensitivity study, no input parameters showed significant interaction effects, which indicates that the model is additive. Because interaction effects were shown to be insignificant, correlation coefficients were not explored further. The fact that all interaction sensitivities are essentially zero indicated that this particular reservoir-to-market benchmark model is an additive model as discussed by Lawal (2007).

Total sensitivity of each input parameter is compared in the bar chart shown in Figure 37. The chemical mixing and injection facility showed the highest sensitivity, followed by surfactant and polymer chemical costs. The central production processing facility and produced fluids processing are also associated with facilities costs, and showed the 4th and 5th highest total sensitivity. The alkali sensitivity rounds out the top 6. The high sensitivity of facilities and chemical cost inputs is shown cumulatively in Figure 38, where both categories each account for slightly more than 40% of the total sensitivity.

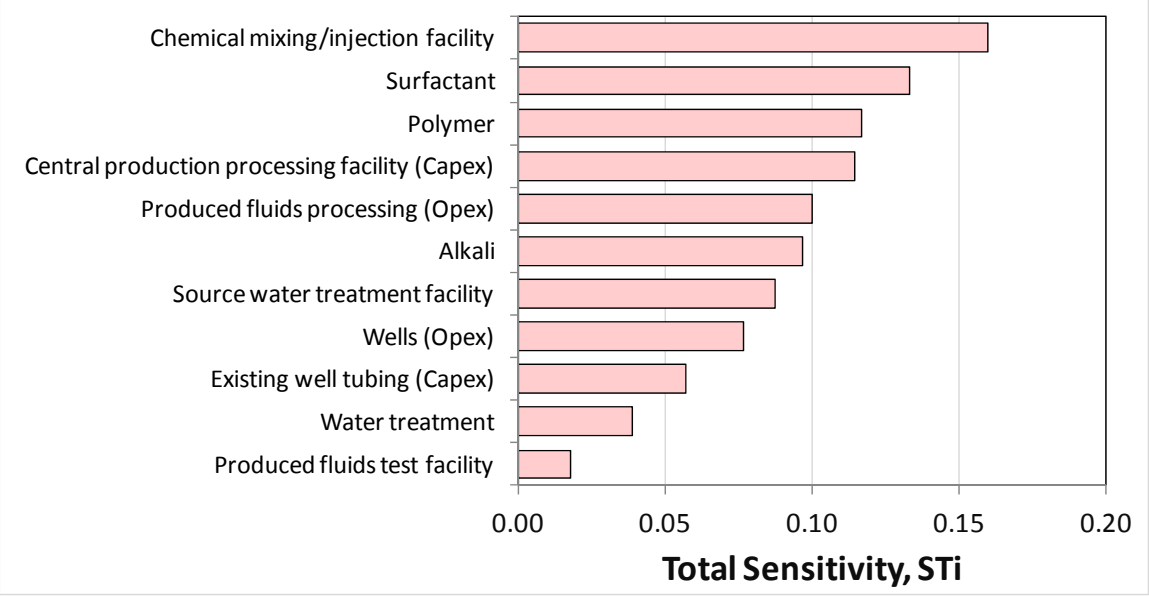

Figure 37: Total sensitivity values for each input parameter.

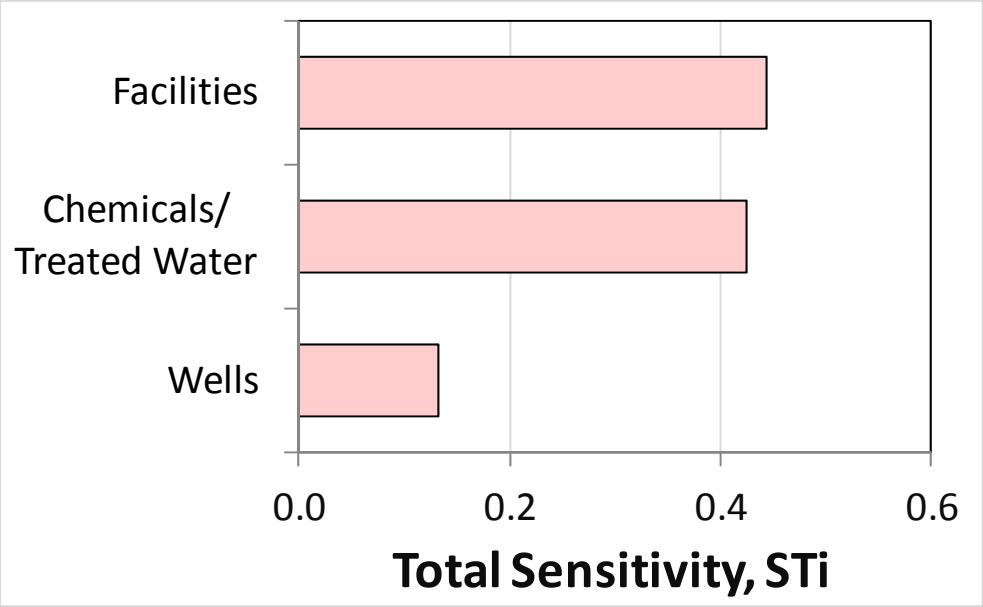

Figure 38: Total sensitivity values for each input category.

Model simplification

Results from the sensitivity analysis can be used to determine how input parameter distributions affect output, and ultimately which input parameter distributions can be omitted given their minimal affect on output. As shown previously, total sensitivity index, S_{T_i}, values obtained from Sobol analysis were used to screen out input parameter distributions as redundant (and therefore fixed at their expected values) if they showed little to no sensitivity on output. By screening out input parameter distributions and only keeping, say, the top six most sensitive parameters, five of the eleven input parameters could be fixed at their expected values. This simplified model can be used for further analysis, such as discretization, with the advantage of saving computational time without affecting output for early reservoir-to-market screening. For some projects, not all input distributions will be normally distributed and will contain a standard deviation

of 10% the expected value. Sensitivity results and model simplification could differ dramatically depending on the input distributions used, which emphasizes the importance of accurately defining input distributions based on sufficient historical data and experience.

Oil price effect on sensitivity analysis

Oil price can have a large effect on sensitivity, and it is important to quantify that effect relative to other parameters in the reservoir-to-market benchmark model. In Chapter 4, oil price was modeled using a mean-reversion (MR) oil price model, and one hundred MR oil price model forecasts were generated and displayed in Figure 18. Ultimately, these oil price forecasts should be used to represent the oil price parameter in the sensitivity analysis; however, it is much easier to represent oil price as a normal distribution like the other parameters. This section shows how the MR oil price model forecasts are used to represent oil price as a normal distribution, then performs a Sobol sensitivity analysis using the simplified model discussed previously.

Oil price as a normal distribution using MR oil price model forecasts

A MR oil price model forecast can show oil price to drastically fluctuate the forecast period, which is what Figure 18 shows over a 15 to 20 year period. When using each of these oil price forecasts in a reservoir-to-market model, the difference in NPV is likely correlated to a mean price and/or weighted mean price that has been weighted by the production fraction (e.g. production for a given month relative to the project lifetime) over a particular price period (e.g. month). For this particular analysis, the simple mean price of each oil price model was used to generate a normal distribution of oil price.

The mean oil price was generated from the monthly price output from each of the one hundred MR oil price model forecasts generated over a 20 year forecast period. The

one hundred mean values were then used to calculate an average and standard deviation to define a normal distribution of the oil price. The average and standard deviation values that were calculated were $101.04 per stock tank barrel and $19.50 per stock tank barrel, respectively.

To perform a similar Sobol sensitivity analysis as done previously, two sets of 10000 oil price values each had to be randomly selected from the oil price normal distribution. These two sets of sampled values along with the oil price normal distribution are displayed in Figure 39. These two sets of 10000 sampled values were combined with the 10000 sampled values from each of ten input parameters used in the previous sensitivity analysis. The produced fluids test facility was removed because it showed low sensitivity, and because the upscaled model later will not contain this input. Another Sobol sensitivity analysis was then performed that included oil price variations.

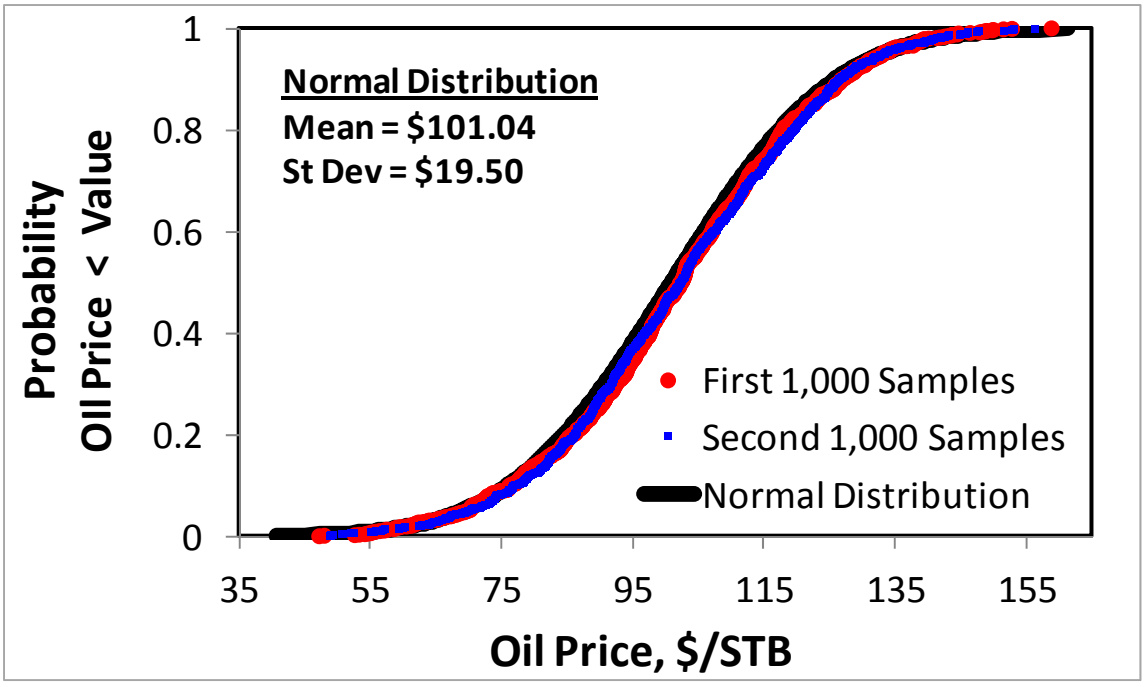

Figure 39: Two sets of sampled values with the oil price normal distribution obtained from MR price model forecasts.

Input parameters and Sobol analysis

In the reservoir-to-market benchmark model, eleven input parameters were defined with probability distributions and used in the sensitivity analysis that included oil price. As done in the previous Sobol analysis, for the purpose of model simplification, these parameters were defined by normal distributions with a mean value being the same as the expected value used previously, and standard deviation of 10% of the mean value. Oil price was also defined by a probability distribution, as was described in the previous subsection. However, the normal probability distribution calculated from the oil price model was found to have a standard deviation of almost 20% of the mean value. Table 16 lists the input parameters and distribution values, which is similar to Table 13 except for the adjustments noted.

The 10000 sampled values (i.e. Monte Carlo iterations) were used perform reservoir-to-market simulations, and the resultant cumulative discounted cash flow NPV (5% discount rate) served as a response variable, with arithmetic mean and variance of arithmetic mean used as statistical estimators. Figure 40 plots the mean and mean variance versus 10000 simulation iterations. The mean has sufficiently stabilized at about 1000 iterations, which is also supported by a near-zero variance.

As done previously, Sobol method results generated the sample mean of model outputs, $E(Y)$, population mean of outputs, $E(Y)^2$, and sample variance, $V(Y)$, which are shown in Table 17, and are used in the Sobol calculations. Table 18 shows the partial variance calculations, U_i, $U_{\sim i}$, and $V\big(E(Y|X_i)\big)$, used in the Sobol analysis, as well as the sensitivity outputs, S_i, S_{T_i}, and $S_{T_i} - S_i$, for each input parameter.

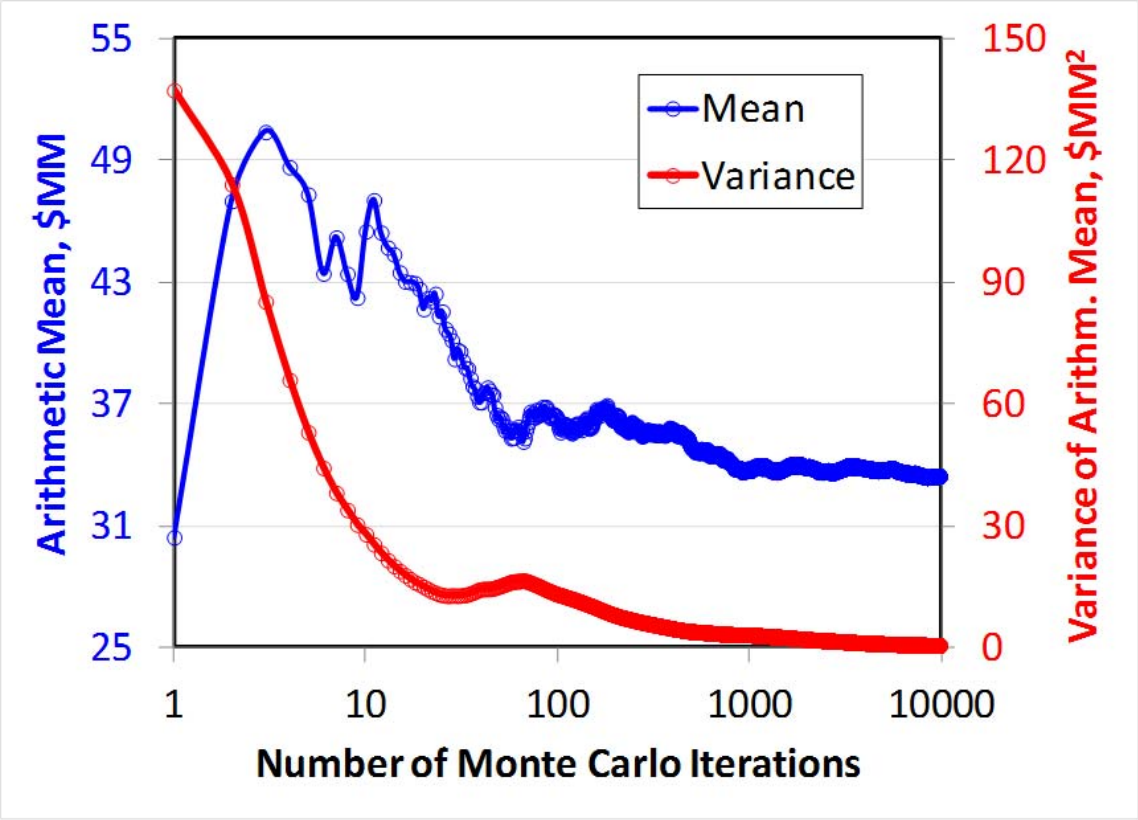

Figure 40: Arithmetic mean and arithmetic mean variance of NPV (using 5% discount rate) for cumulative discounted cash flow versus Monte Carlo iterations.

Table 16: Input parameters and values (mean, standard deviation) defining their normal distribution.

ITEM	VALUE	
	Mean	Stand. Dev.
Oil Price		
Oil Price, $/bbl	101.4	19.5
Well		
Existing well tubing Capex, $MM	0.15	0.015
Well Opex, $k/yr/well	24	2.4
Facilities		
Source water treatment facility, $MM (Capex)	4	0.4
Chemical mixing/injection facility, $MM (Capex)	8	0.8
Central production processing facility, $MM (Capex)	8	0.8
Produced fluids processing, $/bbl (Opex)	0.5	0.05
Chemicals, treated water		
Alkali, $/lb	0.22	0.022
Surfactant, $/lb	1.85	0.185
Polymer, $/lb	1.20	0.120
Water treatment, $/bbl	0.2	0.02

Table 17: Calculated Sobol parameters from the global sensitivity analysis including oil price.

ITEM	VALUE
Sobol Input/Calculated Values	
Sample size, n	10000
Input parameters, k	11
Sample mean of model outputs, E(Y) ($MM)	33.45
Population mean of outputs, $E(Y)^2$ ($\$MM^2$)	1126.11
Sample variance, V(Y) ($\$MM^2$)	217.44

Table 18: Calculated sensitivity values for each input parameter using the Sobol method in the global sensitivity analysis including oil price.

ITEM	SOBOL ANALYSIS VALUES					
	U_i	$U_{\sim i}$	$V(E(Y\|X_i))$	S_i	S_{TI}	$S_{TI} - S_i$
Oil Price						
Oil Price, $/bbl	1338.972	1130.597	212.866	0.979	0.979	0
Well						
Existing well tubing Capex, $MM	1126.517	1343.131	0.411	0.002	0.002	0
Well Opex, $k/yr/well	1126.464	1342.851	0.358	0.002	0.003	0
Facilities						
Source water treat. facility, $MM (Capex)	1126.533	1342.777	0.427	0.002	0.004	0
Chemical mixing/inj. facility, $MM (Capex)	1127.353	1342.294	1.247	0.006	0.006	0
Central prod. process. facility, $MM (Capex)	1126.793	1342.855	0.687	0.003	0.003	0
Produced fluids processing, $/bbl (Opex)	1126.351	1342.958	0.245	0.001	0.003	0
Chemicals, treated water						
Alkali	1126.126	1343.522	0.020	0.000	0.000	0
Surfactant	1126.888	1342.427	0.782	0.004	0.005	0
Polymer	1126.415	1342.905	0.309	0.001	0.003	0
Water treatment	1126.189	1343.458	0.084	0.000	0.000	0

The sensitivity analysis results in Table 18 clearly show that oil price accounts for almost all of the total sensitivity, with a S_{Ti} value of 0.979. Although the standard deviation used to define the oil price distribution was 20% of the expected value (versus 10% for all other parameters), such a high total sensitivity value of 0.979 results from oil price inherently having a large influence on the model (rather than twice as wide of a normal distribution). There were no interaction effects between the parameters, as shown by all zero values for the $S_{Ti} - S_i$ column in Table 18. As discussed previously, Lawal (2007) discusses additive and non-additive input-output relationships, and how interaction effects are essentially zero with an additive model. The fact that all interaction sensitivities are essentially zero indicated that this particular reservoir-to-market benchmark model is an additive model.

A more simplistic representation of the effect oil price has on the reservoir-to-market model compared to other input parameters is shown in Figure 41. A model using all expected values is designated as a ‘P50’ case in the plot, which is represented by a black line. The ten parameters, exclusive of oil price, represented by normal distributions in the sensitivity analysis are all set to either P90 or P10 values. The result of these P90 and P10 simulations is shown by the dashed blue lines in Figure 41. Similarly, only oil price was varied to either a P90 or P10 value while keeping all other input parameters at expected values, and these results are shown by the dashed red lines. From this analysis, the results clearly show that oil price alone has a much greater sensitivity than all other input parameters combined.

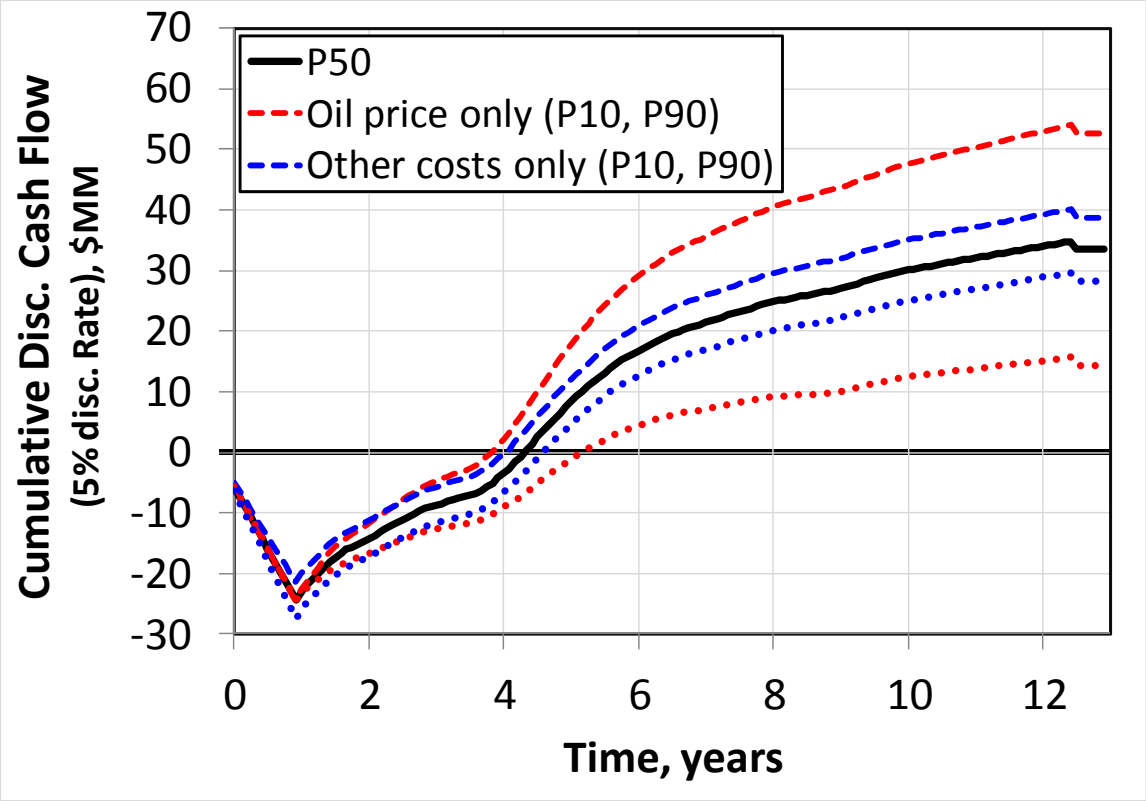

Figure 41: Cumulative disc cash flow (5% disc. rate) of the reservoir-to-market model expected values (P50), only varying oil price (P10/P90 - top/bottom blue), and only varying other relevant costs (P10/P90 - top/bottom blue) with oil price at expected value

DISCRETIZATION

As discussed previously, many input parameters for a reservoir-to-market model are continuous. Discretization of a continuous range may appear more accurate if a large number of discretization intervals are used. Several discretization methods can be used that can accurately represent continuous ranges with relatively few discretization intervals/values, their approximation error, and how they compare to Monte Carlo simulation (Bickel et al.,2011).

Gaussian quadrature is the most accurate general method for moment matching, and the theoretical framework described here will revolve around that method. A 2-, 3-, 4-point, etc. discretization of a PDF is ultimately summarized as percentages of values on an excess distribution function (EDF), which is the complement of a cumulative distribution function (CDF). P10, P50, and P90 are common EDF values used in the oil and gas industry, which represent 10%, 50%, and 90% of the EDF. An example discretization (e.g. Swanson's mean) uses probabilities of 0.3, 0.4, and 0.3 for P10, P50, and P90, respectively (Bickel et al., 2011).

In addition to the general Gaussian quadrature method, Bickel et al. (2011) discussed more customized discretization methods (e.g. bracket mean and bracket median methods) that use the specific CDF of the input parameter, rather than distributions that may not belong to any common distribution family. This section will discuss the theoretical framework for general discretization and several short-cut methods, which will be applied for model simplification and decision analysis.

Theoretical framework for method of moments discretization

Bickel et al. (2011) explains the process and application of discretization to represent a continuous probability density function with a set of values. A given probability density function (PDF), $f(x)$, can be approximated with a set of values $x_i \in X, i = 1,2, \dots, N$, and associated probabilities $p_i = p(x_i)$. For Monte Carlo simulation, x_i values are randomly selected from the sample space X based on their defined PDF; however, the objective of discretization is to accurately select a few x_i values (e.g. 2-, 3-, or 4-point) with associated probabilities to represent a continuous distribution. Several discretization methods simplify a continuous distribution, X, to about 3 points, while still representing the properties of X.

Method of Moments Discretization

Raw moments measure a distribution about the origin (mean), with the kth raw moment of X with PDF $f(x)$ expressed as: $\mu_k = E[X^k] = \int_X^{\cdot} x^k f(x)dx;\ k = 0,1,2, ...,$ where $E[-]$ is the expectation operator. For example, the first raw moment, μ_1, is the mean. Central moments measure the distribution about the mean, with the kth central moment expressed as: $m_k = E[(X - \mu_1)^k] = \int_X^{\cdot}(x - \mu_1)^k f(x)dx;\ k = 0,1,2, ...$ For example, the second central moment, m_2, is also the variance (symbolized as σ^2). A relationship between raw and central moments is (Papoulis, 1984): $m_k = \sum_{j=0}^{k} \binom{k}{j} (-1)^{k-j} \mu_j \mu_1^{k-j}$. Skewness (measure of asymmetry) and kurtosis (measure of distribution peakedness) are common normalized central moments, and are $\gamma_3 = m_3 m_2^{-3/2}$ and $\gamma_4 = m_4 m_2^{-2} - 3$, respectively (Bickel et al., 2011).

Bickel et al. (2011) describes the insufficiency of calculating the expected value of a value function of interest using only raw moments, and therefore details a discretization approach based on Gaussian quadrature. For a input PDF $f(x)$ and function $\Omega(x)$, a finite sum integral can be approximated as: $\int_X^{\cdot} f(x)\Omega(x)dx = \sum_{i=1}^{N} p_i \Omega(x_i)$; consisting of N values of X, with each x_i weighted by probability p_i.

For the analysis, $\Omega(x_i) = x_i^k;\ k = 0,1,2, ...$ is assumed for the kth raw moment of X, and therefore the expected parameters of interest are: $E[X^k] = \sum_{i=1}^{N} p_i x_i^k\ ;\ k = 0,1,2, \dots, N$. This Gaussian quadrature approximation process is called moment matching, and the relevance is that N points can match $2N$ moments of X, which includes $k = 0$. Therefore, a three-point approximation matches moments of $k = 0\ to\ 5$, which accurately represent mean, variance, skewness, and kurtosis of a continuous PDF (Bickel et al., 2011).

Short-cut discretization methods

Several common discretization short-cut methods are discussed in Bickel et al. (2011). Pearson and Tukey (1965) recommended a three-point mean approximation of 0.185, 0.630, and 0.185 for P95, P50, and P5, respectively, for several distributions (normal, beta, gamma, inverse gamma, and Student's t) that were not highly skewed. The Standford Research Institute (SRI) discretized a normal distribution to approximately 0.25, 0.50, and 0.25 for P10, P50, and P90. The Swanson mean was found empirically for moderately skewed distributions, and approximated probabilities of 0.30, 0.40, and 0.30 for P10, P50, and P90 (Megill, 1984). However, Swanson's mean in particular, was not intended to approximate higher moments or serve as a complete discretized distribution; a method that approximates the mean does not necessarily approximate the whole PDF (Bickel et al., 2011). Other short-cuts based on Gaussian quadrature, bracket median/mean and/or equal weighting of the CDF are shown in Miller and Rice (1983), D'Errico and Zaino (1988), Zaino and D'Errico (1989), and Taguchi (1978).

Obtaining discretization values and probabilities

If a distribution is known exactly, moment-matching calculations can provide accurate discretizations. Sometimes though, distributions are not known exactly, and must be either approximated or discretized by other methods (e.g. bracket methods). In fact, moment-matching discretization approximations match exactly the PDF properties (e.g. mean, variance, skewness, and kurtosis) given sufficient moments and assuming one of the distributions mentioned, making the discretization approach very accurate. Accuracy comparison relative to Monte Carlo simulation will be discussed further in the following subsection. Furthermore, what is interesting is that short-cut methods can still have a comparable accuracy to an equivalent number of Monte Carlo iterations, as determined by the S-equivalence discussed in the next subsection. In general, short-cut

based approaches can reasonably approximate normal distributions, but are highly inaccurate for log-normal and moderate to highly skewed distributions, which are common for reservoir properties. Transforming the log-normal to a normal distribution can help alleviate some of this error (Bickel et al., 2011; Miller and Rice, 1983). Using the common percentages used in the oil and gas industry: P10, P50, and P90; Table 19 lists the weights and/or probabilities for four common distribution types (uniform, normal, exponential, and triangular).

Table 19: Discretization weights for P10, P50, and P90 values for various distributions (Bickel et al., 2011).

	Uniform	**Normal**	**Exponential**	**Triangular**
	$f(x) = 1$	$f(x) = (2\pi)^{-\frac{1}{2}} e^{-\frac{1}{2}x^2}$	$f(x) = e^{-x}$	$f(x) = \begin{cases} \frac{2(x-a)}{(b-a)(c-a)} & a \le x \le c \\ \frac{2(b-x)}{(b-a)(b-c)} & c < x \le b \\ 0 & \text{otherwise} \end{cases}$
	$x \in [0,1]$	$x \in (-\infty, \infty)$	$x \ge 0$	$x \in [a = 0, b = 1, c = 0.5]$
P10	0.260	0.304	0.360	0.273
P50	0.480	0.392	0.175	0.454
P90	0.260	0.304	0.465	0.273

Accuracy and error in Monte Carlo sampling versus discretization

In the real world, many input parameters for a reservoir-to-market model are continuous. For example, most if not all of the price inputs defined, such as chemical costs, are determined by market conditions, which can fluctuate continuously based on supply/demand economics. Therefore, one may assume that representing input parameters by continuous probability density functions would be most accurate. However, it is generally more difficult or computationally intensive to use continuous

rather than discrete parameters, and both parameter representations are subject to error. Additionally, a multi-stage decision-tree with two or more dependent input parameters at different stages can complicate Monte Carlo simulation (Bickel et al., 2011).

Because discretization of a continuous variable approximates a value across each interval, the discretization method induces approximation error (Bickel, 2011). However, although Monte Carlo simulation can use continuous distributions, sampling of these distributions makes the Monte Carlo method subject to sampling error. Bickel (2011) assessed the approximation and sampling errors in these methods to determine which method achieved the best accuracy. Ultimately, discretization and Monte Carlo methods were found to have similar error at a particular S-equivalence, where S is the equivalent number of Monte Carlo samples (Bickel, 2011). Surprisingly, the S-equivalence was found to be large enough to where discretization was the preferred and computationally simpler alternative. Bickel et al. (2011) shows a derivation for calculating S-equivalences based on the central limit theorem, and compares first (mean), second (variance), and third (skewness) moment S-equivalences of six different short-cut discretizations for uniform, normal, triangular, exponential, and logarithmic distributions. The results are surprising, and for several short-cut methods, show tens to hundreds of thousands of Monte Carlo simulations are required for the same error, which highlights the accuracy of a short-cut method or method of moments over Monte Carlo simulation (assuming the distribution is known). The reader can refer to Bickel et al. (2011) for a derivation of equations to calculate S-equivalence for several standard distributions.

DECISION ANALYSIS

Decision theory can provide a rational framework for decision-making (Min, 2008). It aims to find the most preferred option among a set of options, with the optimum

solution having the largest measure of satisfaction. A consequence of the satisfaction is some degree of utility, or measurement of value (e.g. NPV), and the objective is generally to maximize the utility. Min (2008) and Kelsey and Quiggin (1992) outlined decision criteria and terminology. A decision problem is defined with a certain number, n, of options, or alternatives (A1, A2,…,An), along with m states of nature (S1, S2, …, Sm).

Each state of nature has a probability associated with it (P(S1), P(S2),…,P(Sm)), and resultant output for each state of nature for a particular alternative has a consequences of utility (uij, i=1,2,…,n; j=1,2,…,m). Figure 42 shows a basic decision tree with the mentioned components.

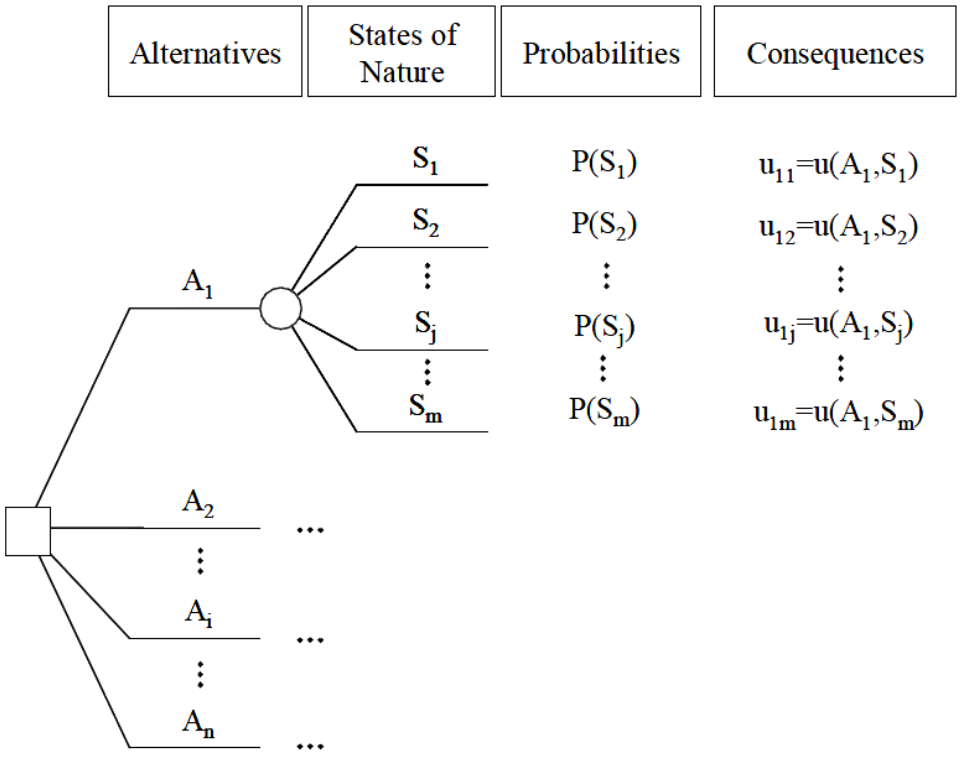

Figure 42: Basic decision tree representing various alternatives and states of nature, with associated probabilities, as well as the consequence, or utility, of resultant output (Min, 2008).

From Figure 42, a common representation in a decision tree is for squares to represent decision nodes, and circles as chance nodes. Several different alternatives stem from a decision node, and the alternative with the greatest utility will ultimately be selected. Several different states of nature stem from a chance node, each with different probabilities of occurrence. In Figure 42 each branch representing a separate state of nature has a utility associated with it as well as a probability. The value of the alternative A1 branch can be calculated by summing the products of each state of nature by their respective utility as such:

$$u_1 = u(A_1) = \sum_{j=1}^{m} P(S_j)u(A_1 S_j)$$

After calculating the utility summations of each of the alternative branches, the branch with the greatest utility should be selected in the decision tree analysis.

DECISION TREE ANALYSIS APPLICATION WITH DISCRETIZATION

The reservoir-to-market model simplified from the Sobol analysis can be simplified further through discretization. From the Gaussian quadrature method of moments, a 3-point discretization of the normal distributions of input parameters into P10, P50, and P90 was considered. Again, P10, P50, and P90 values correspond to 10, 50, and 90% of an excess distribution function (EDF). Additionally, probability values from the Gaussian quadrature are 0.304, 0.392, and 0.304 for P10, P50, and P90, respectively.

Table 20 lists the relevant input parameters kept from the Sobol analysis, and their mean and standard deviation values. The P10, P50, and P90 values are listed as well, and

each of these represents a value for the 3-point discretization, which essentially gives three different states of nature for each input parameter.

Figure 43 shows a decision tree with each of these uncertain input parameters as chance nodes. Considering Alternative 1 stemming off a decision node, many of the chance nodes are not shown for simplification. However, if three different states of nature exist for each input parameter, then with sixn input parameters the overall states of nature will equal: $3^6 = 729$ total states of nature. Therefore, to completely represent the 3-point discretization outcomes for six different input parameters, 729 different model runs are performed.

Table 20: Input parameters used for the 3-point discretization, and their normal distribution values.

ITEM	VALUE				
	Mean	Stand. Dev.	P90	P50	P10
Chemical mixing/inj. facility, $MM (Capex)	8	0.8	6.97	8	9.03
Central prod. processing facility, $MM (Capex)	8	0.8	6.97	8	9.03
Produced fluids processing (Opex)	0.5	0.05	0.436	0.5	0.564
Alkali, $/lb	0.22	0.022	0.192	0.22	0.248
Surfactant, $/lb	1.85	0.185	1.61	1.85	2.09
Polymer, $/lb	1.2	0.12	1.05	1.20	1.35

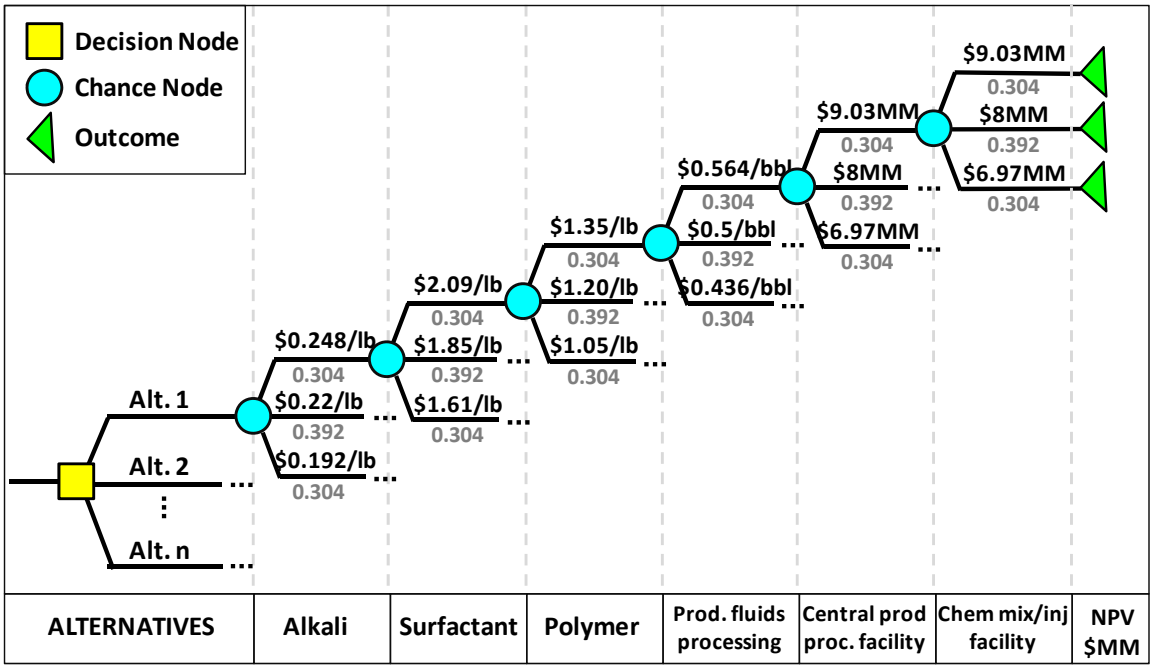

Figure 43: Decision tree structure for the 3-point discretization of different input parameters (with values in black and weights in grey).

Results of the 729 model runs using discretization can be analyzed further to understand the distribution of NPV, the range of cumulative discounted cash flow, and ultimately the value of the decision tree branch for Alternative 1. Figure 44 shows the CDF of NPV (at 5% discount rate), which indicates normally distributed output.

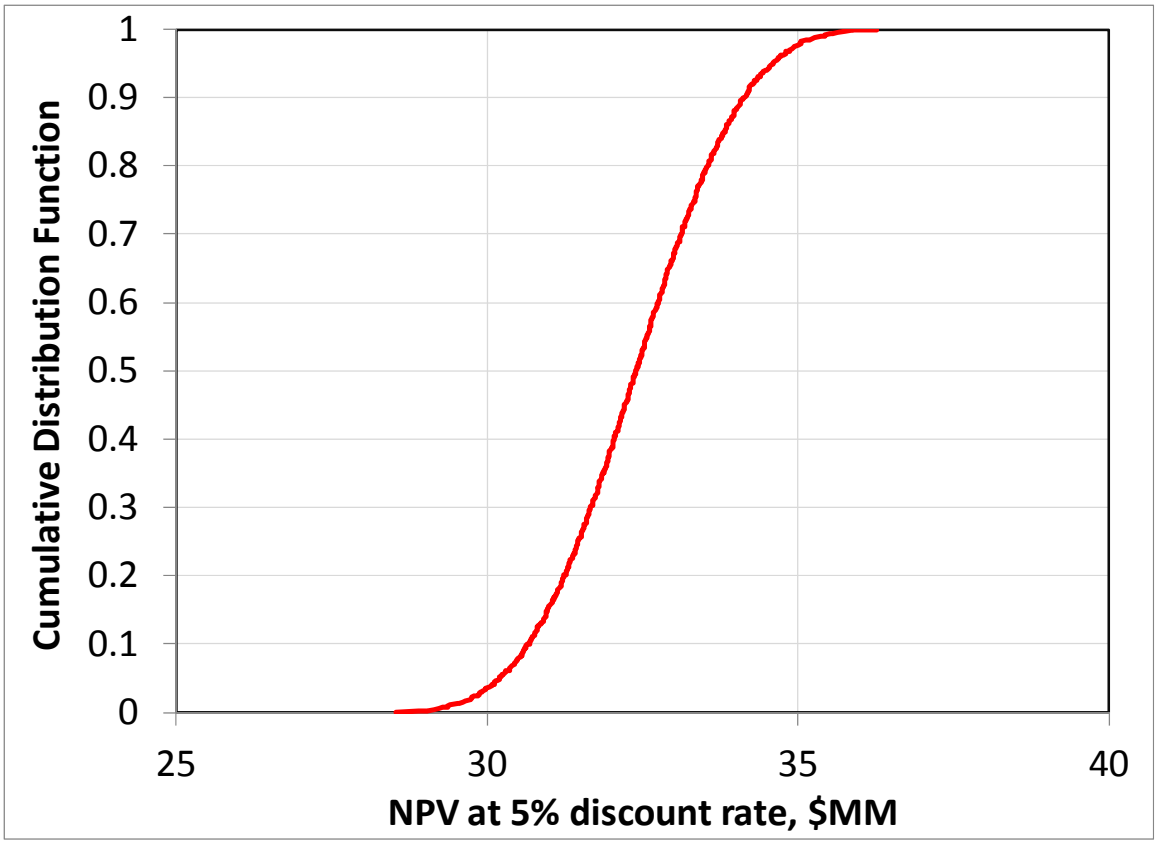

Figure 44: Cumulative distribution function of NPV (5% discount rate) generated from 729 discretization runs.

DEVELOPMENT SCENARIO APPLICATION

The use of decision trees allows for several different development scenarios to be analyzed that relate to different project development approaches. Essentially, decision nodes corresponding to different development alternatives can be thought of as alternative development scenarios, and are assessed using development scenario analysis. The scope of development scenario analysis in early screening can assess a wide range of different project possibilities. By using a reservoir-to-market model and a decision tree

approach, the simplification techniques explored previously, such as global sensitivity analysis and discretization, can help speed the screening process.

This section will explore a development scenario analysis application by considering chemical flooding with conventional and novel alkali. As discussed previously, novel alkali can provide an advantage in reducing water treatment costs, though the novel alkali itself generally costs more than conventional alkali (and has additional risks/uncertainty). Another advantage may be cost savings in the source water treatment facility, as not as much equipment for treating source water will be required.

SCENARIO / DECISION TREE ANALYSIS FRAMEWORK

As discussed previously, the purpose of decision tree analysis is to calculate an overall risk-weighted project value given results from several different development scenarios. A decision tree layout contains a series of nodes and branches, with the branches being either intermediate branches, from one node to another, or end branches, from a node to an end result. Each end result represents a development scenario and has an associated value obtained from running a reservoir-to-market economic model.

A decision node represents a point at which a decision is made (e.g. selecting either conventional or novel alkali), and has a value that is the highest of its branches, given that one would always make the decision of greatest value. Decision nodes are generally discrete, for example either a decision is taken or not, or one particular decision is taken. Branches stemming from a decision node are various alternatives. A chance node represents a point where more than one possible state of nature can occur, with each branch feeding into the node having an associated probability and value. Branches from chance nodes are commonly expressed with discrete probability values (obtained from discretization), although chance nodes can be expressed as distributions. The overall

value of a chance node will be the sum of the probability weighted average of the associated branches.

DEVELOPMENT SCENARIO ALTERNATIVES AND STATES OF NATURE

A simplistic development scenario application assesses the different alternatives of either a conventional or novel development approach with respect to alkali. The decision tree shown previously in Figure 43 detailed the branching of 729 different states of nature for a particular development scenario known as Alternative 1, though a total of n Alternatives were shown in the figure. These states of nature could be collapsed, and the development Alternatives simplified to contain only three of interest: conventional alkali, novel alkali, and no chemical flooding. A simplified decision tree is shown in Figure 48 with these components. No chemical flooding in this case will imply a scenario where nothing occurs (i.e. NPV = $0), rather than an ordinary waterflood or another routine production scenario.

For the conventional and novel alkali scenarios, three parameter values were changed: the cost of the alkali, water treatment, and source water treatment facility. Table 21 shows the costs of these parameters. The novel alkali scenario will have an alkali cost twice that of the conventional alkali, with an expected value at $0.44/lb compared with $0.22/lb. However, savings will occur on the water source costs, as water used for novel alkali may not have to undergo expensive desalination and/or softening compared to conventional alkali. Therefore, no water cost will be used for the novel alkali scenario, compared with $0.20/bbl for the conventional alkali. Additionally, the novel alkali scenario will have half the source water treatment facilities costs at $2 million Capex, compared to $4 million Capex for the conventional alkali scenario. Only the alkali will have a distribution in the analysis because the treated water and source water treatment

facility showed comparatively low sensitivity, and are therefore fixed at their expected values.

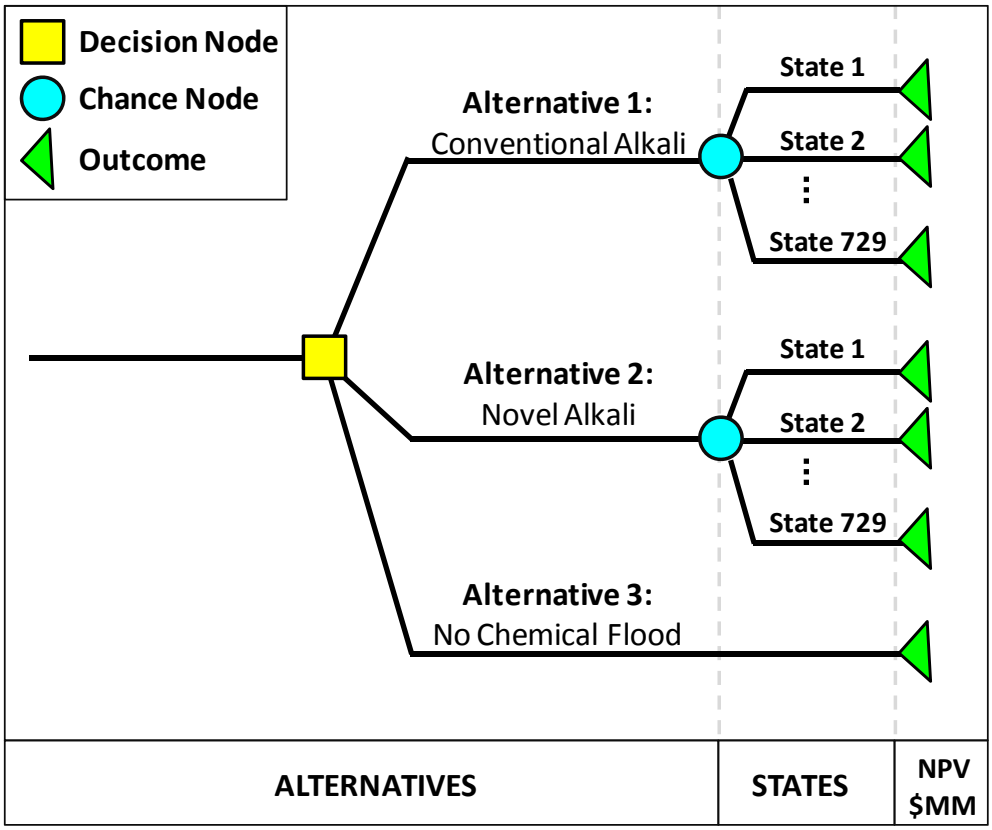

Figure 45: Decision tree structure for two alternative flooding scenarios (conventional and novel alkali), each with 729 states of nature, and a no flooding scenarios.

Table 21: Parameter input differences for conventional alkali and novel alkali project scenarios.

ITEM	VALUE	
	Mean	Stand. Dev.
SCENARIO 1: Conventional Alkali		
Conventional Alkali, $/lb	0.22	0.022
Treated Water, $/bbl	0.2	-
Source water treatment facility, $MM (Capex)	4	-
SCENARIO 2: Novel Alkali		
Novel Alkali, $/lb	0.44	0.044
Treated Water, $/bbl	0	-
Source water treatment facility, $MM (Capex)	2	-

DEVELOPMENT SCENARIO RESULTS AND DISCUSSION

Comparing conventional and novel alkali scenarios is relevant because novel alkali can help reduce the Opex of source water by minimizing the need for water treatment (e.g. water softening); however, it may increase the alkali Opex of the novel alkali because it is more expensive than a conventional one.

Reservoir-to-market models for the novel alkali scenario were run for all cases, and the results were compared to the conventional alkali scenario. Figure 46 compares the cumulative distribution functions of NPV (5% discount rate) for both the conventional and novel alkali scenarios. The novel alkali curve is shifted towards a less positive NPV that is therefore less favorable than the conventional alkali scenario.

Figure 47 plots P50 curves of cumulative discounted cash flow (using a 5% discount rate) of the two alkali scenarios to allow visualization of changing project valuation over time. The two curves follow typical cumulative discounted cash flow curves for a project, with an initially large capital expense at the beginning of the project,

followed by gradual increasing cumulative discounted cash flow over the project lifetime. When considering the discretization weights for the various branches of chance nodes representing all 729 cases in the decision tree, the NPV of the conventional and novel alkali scenarios (Alternatives 1 and 2 branches in Figure 48) are calculated to be $32.4 and 31.7 million, respectively. Figure 47 compares the P50 cumulative discounted cash flow curves for conventional and novel alkali scenarios. At the end of the project, the conventional alkali scenario plot is slightly higher than the novel alkali plot, which explains the differing cumulative distribution functions in Figure 46.

Although the NPV for the novel alkali scenario may be similar to the conventional alkali scenario, there is often greater risk and uncertainty with a novel approach. This greater uncertainty can be captured in the distribution ranges of model input parameters, which in this case was not performed because all distributions were normal distributions with standard deviations of 10% of the mean.

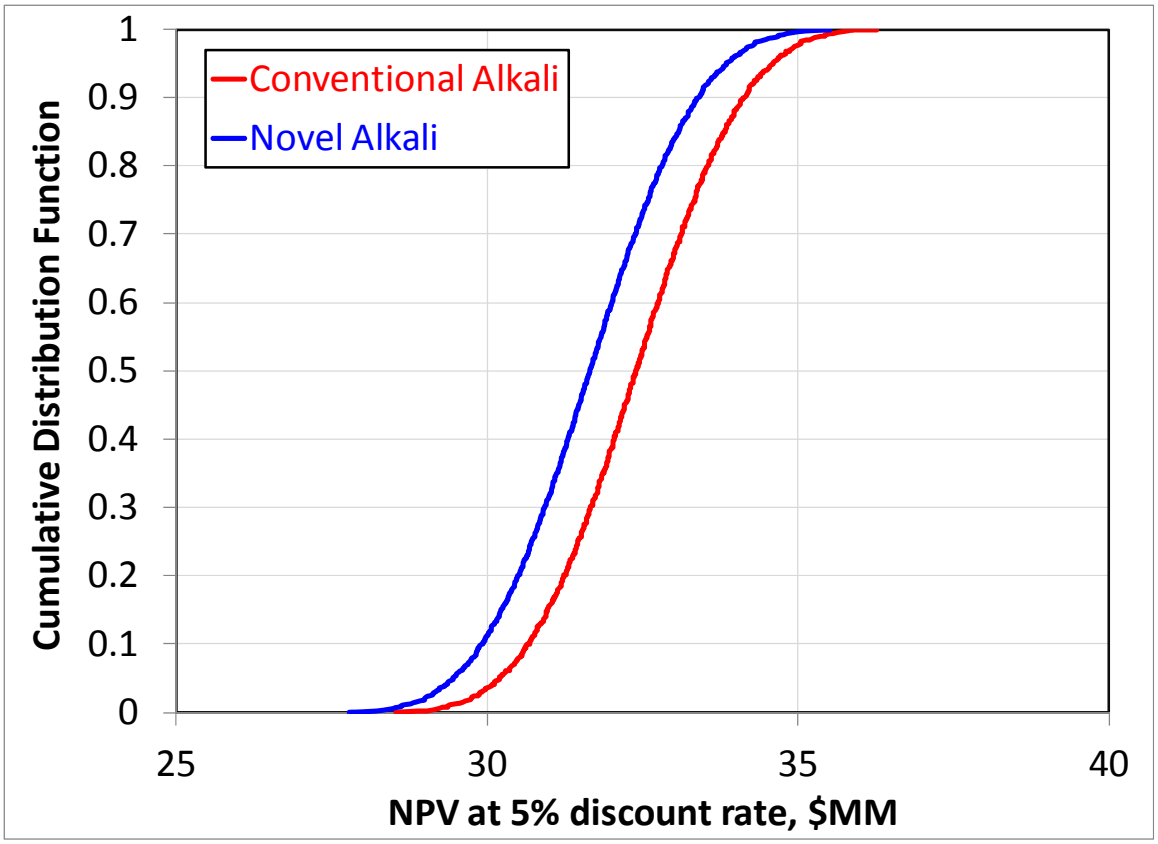

Figure 46: Cumulative distribution function of NPV (5% discount rate) generated from 729 discretization runs for both conventional and novel alkali scenarios.

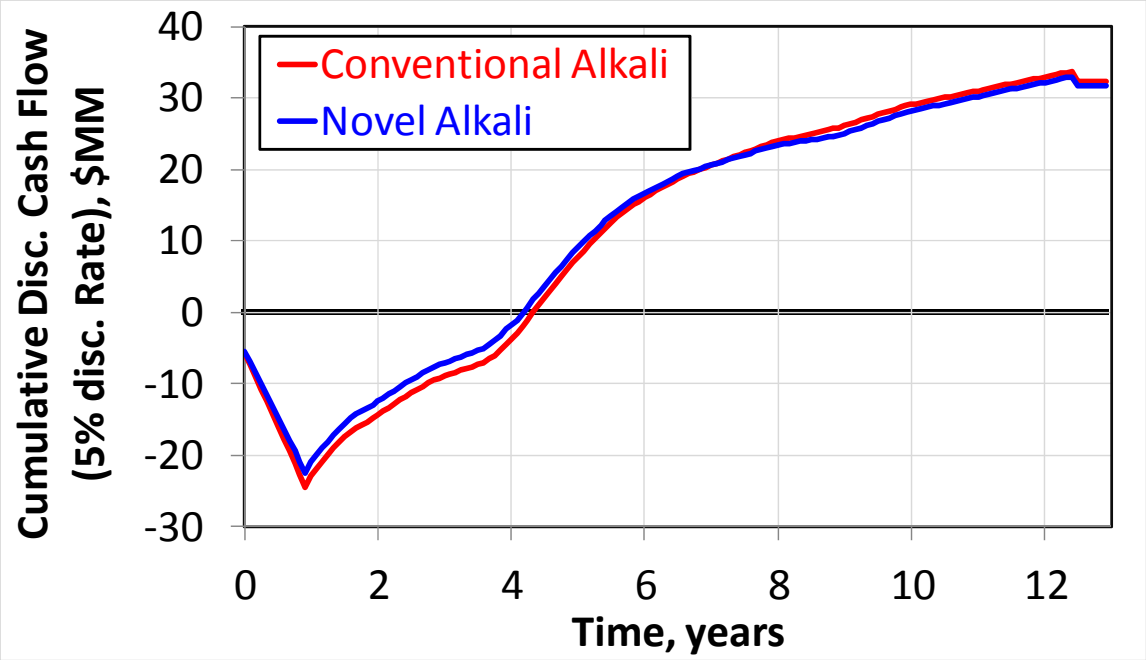

Figure 47: Comparison of the P50 cumulative disc. cash flow (5% disc. rate) curves for conventional and novel alkali scenarios, generated from the 729 discretization runs.

The conventional and novel alkali results (as well as no flood scenario) are shown in the decision tree, and represented with their NPV value (using a 5% discount rate). As calculated previously, when weighting the 729 cases according to 3-point discretization of 6 input parameters, the conventional, novel, and no flood scenarios have NPV values of $32.4 million, $31.7 million, and $0, respectively. These three scenario branches meet at a decision node, which ultimately decides on whichever project has the highest NPV. In this case, the conventional alkali scenario has the highest NPV, and will therefore be selected as the most profitable and feasible project (assuming all uncertainty has been captured). This assessment has not necessarily been to prove that conventional alkali is economically more feasible than novel alkali, but rather to demonstrate how projects are valued and uncertainty is assessed.

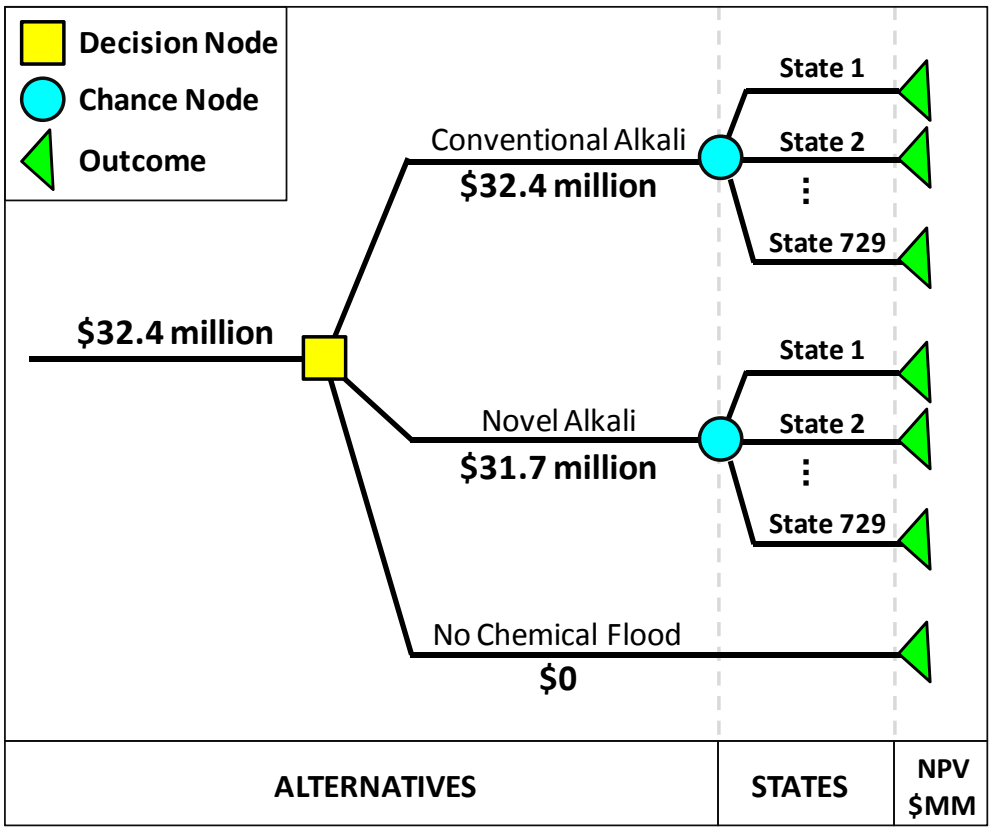

Figure 48: Decision tree comparing conventional and novel alkali, and no flood scenarios using NPV (5% discount rate) as the decision criteria.

SUMMARY AND CONCLUSIONS

Uncertainty of input parameter cots in the reservoir-to-market benchmark model were characterized by continuous normal distributions, and these formed the basis of the sensitivity analysis, model simplification, discretization, and decision-making in this chapter. This represented additional model tuning from the original benchmark model, helping to understand potentially simplify the model prior to upscaling. A global sensitivity analysis was performed using Monte Carlo analysis and the Sobol method,

which identified specific inputs having the least and greatest sensitivity on project economics. Global sensitivity analysis helped eliminate the need to include distributions of some input parameters because their sensitivity was small relative to the total. Discretization helped simplify the model further by approximating input distributions with three weighted values, rather than a distribution at which, say, 1000 samples would need to be taken from in order to represent the distribution. Furthermore, discretization was used in decision tree analysis, which helped assess and compare multiple project scenarios to determine which was most economically feasible.

The Sobol sensitivity analysis randomly sampling each input distribution 1000 times, which was shown to be the iteration number at which mean output NPV stabilized and variance became nearly zero. The chemical mixing and injection facility showed the highest sensitivity, followed by surfactant and polymer chemical costs. The central production processing facility and produced fluids processing are also associated with facilities costs, and showed the 4^{th} and 5^{th} highest total sensitivity, with the alkali sensitivity being sixth highest of 11 input parameters. Total sensitivity was between about 0.1 and 0.15 for each of the six input parameters showing the highest sensitivity. Both facilities and chemical cost inputs cumulatively showed the highest sensitivity, with each category accounting for more than 40% of the total sensitivity.

Oil price models were used to generate a normal distribution for oil price, which was subsequently sampled for Sobol analysis. Oil price was shown to dominate sensitivity, accounting for about 98% of total sensitivity when ten additional parameters were assessed. This not only showed the dominant effect of oil price on sensitivity, but the importance of fixing oil price when determining how sensitivities of other input parameters compare to one another.

For the discretization analysis, only the 6 input distributions were kept from parameters showing highest sensitivity, while the other five parameters were fixed at their expected values. This simplified the number of model runs to $3^6 = 729$ when using 3-point discretization. Discretization was demonstrated in a decision-tree analysis using two different scenarios for conventional and novel alkali. Alkali costs for novel alkali were assumed to be twice as high, but costs were saved in no water treatment costs and half the source water treatment facility Capex. Regardless, the novel alkali scenario was still shown to have a lower NPV of $31.7 million compared to the conventional alkali NPV of $32.4 million.

CHAPTER 8: UPSCALING A MULTI-PATTERN PILOT TO COMMERCIAL SCALE USING RESERVOIR-TO-MARKET MODELING

INTRODUCTION

A reservoir-to-market model benchmark can be used to generate a commercial-scale project valuation. Of course, the more information known about the specific field, the more accurate the upscaled reservoir-to-market model will be. Having field-specific production performance data, whether from a single- or multi-patterned pilot, can be crucial to a model, as this information ultimately determines expected recoverable volumes and rates, and surface facilities design. This chapter discusses the process of upscaling a reservoir-to-market model benchmark that has already been tuned to a specific field and calibrated with a multi-patterned pilot, with the objective of valuing a commercial-scale chemical flood.

UPSCALING THE RESERVOIR-TO-MARKET BENCHMARK MODEL

The basic categories described in Chapter 6 to build the reservoir-to-market model will be modified here to account for upscaling, and include reservoir fluids and volumes, well patterns, well performance, facilities (including pipes), rigs, scheduling, and costs.

RESERVOIR AND WELLS

This section describes basic reservoir and well inputs referenced from a multi-patterned ASP flood analogue used for the benchmark in Chapter 6, including subsections relating to: field area and well patterning, reservoir dimensions and volumetrics, and well performance.

Field area and well patterning

The reservoir-to-market benchmark model from Chapter 6 used a total of 9 five-spot well patterns, which contained 17 injectors and 9 central producers (as was shown in Figure 20). The well spacing was 354 m between producers, and therefore each five-spot pattern had an area of approximately 0.123 km^2 for a total field area of about 1.11 km^2 for 9 five-spots. This is approximately 30 acres for each five-spot pattern. The upscaled model will contain 100 five-spot patterns, which is 121 injectors and 100 producers. The well spacing will be kept the same at 354 m between producers (i.e. 0.123 km^2 per five-spot), making the total field area about 111 km^2. Figure 49 shows a general layout of all 121 injectors and 100 producers (each in the center of a five-spot pattern).

The central processing facilities are located in the middle of the field, which is essentially in the middle of four quadrants of 25 five-spot patterns each. Fluids from all 100 producers would ultimately feed into the central processing facility. Figure 50 shows this arrangement for one of the four 25 producer well groups, along with the injection and production pipe network.

For the whole field layout, all four of the 25 producer well groups can be arranged in four different quadrants, with the facilities located at the center. Figure 51 shows this arrangement not drawn to scale, with the facilities drawn much larger for visual clarity. The four quadrants are simply shown as smaller images of what exists in Figure 50, and in an actual setting, the facilities would cover roughly the area of one five-spot.

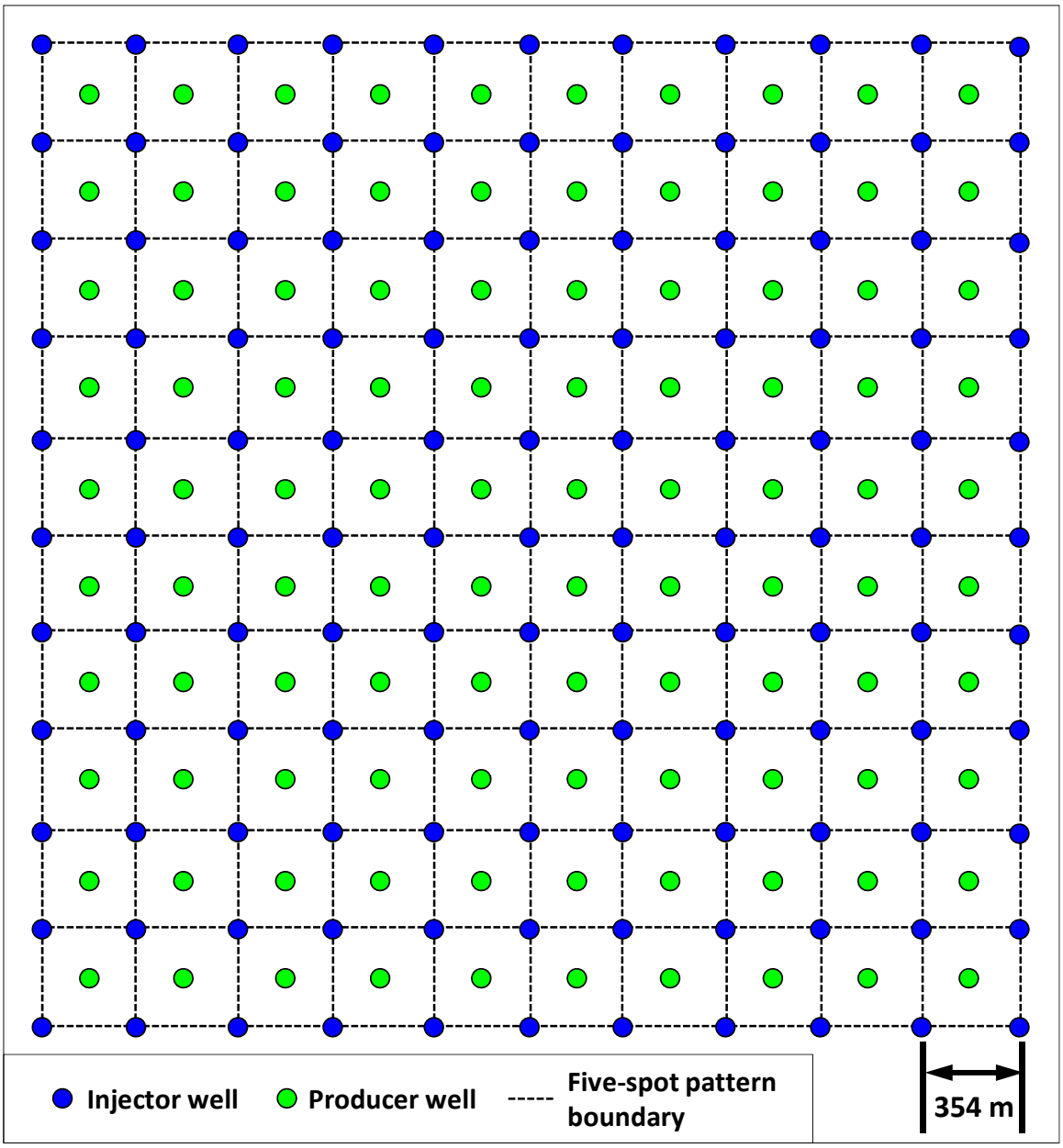

Figure 49: Well patterning for upscaled model, which contains 100 five-spot patterns (121 injectors and 100 producers).

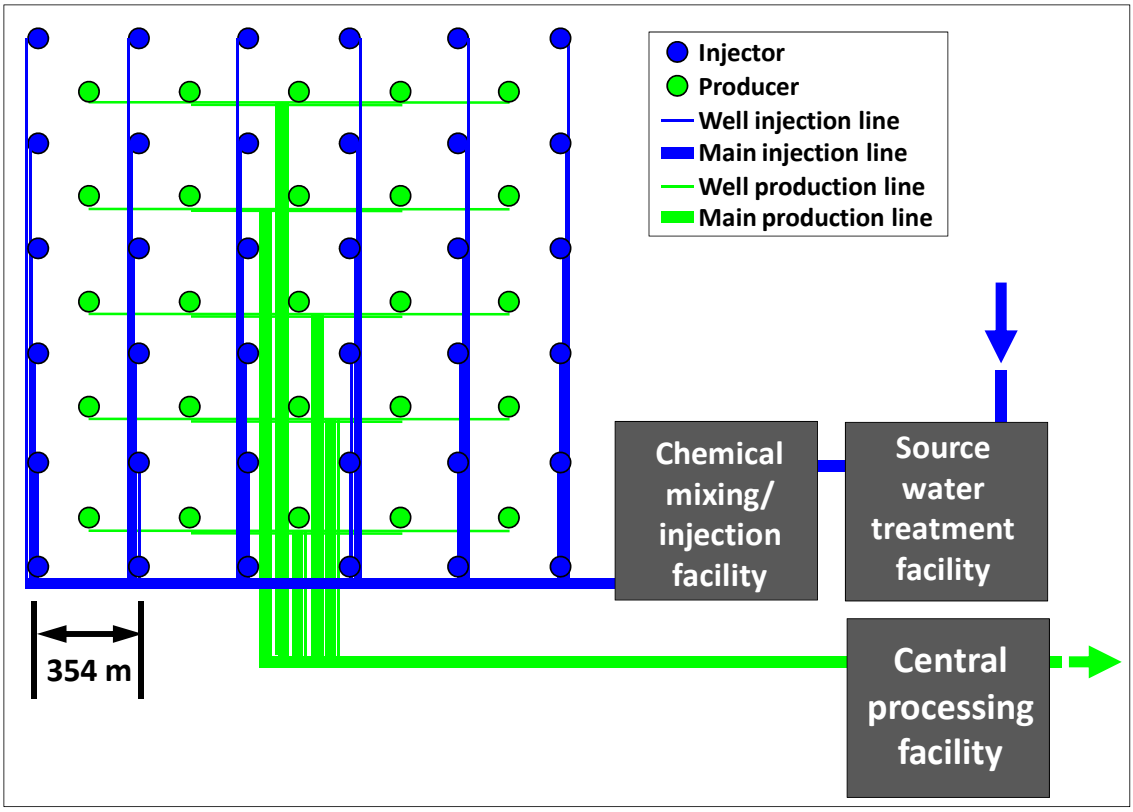

Figure 50: One of four patterns used in the upscaled model with 25 producer wells.

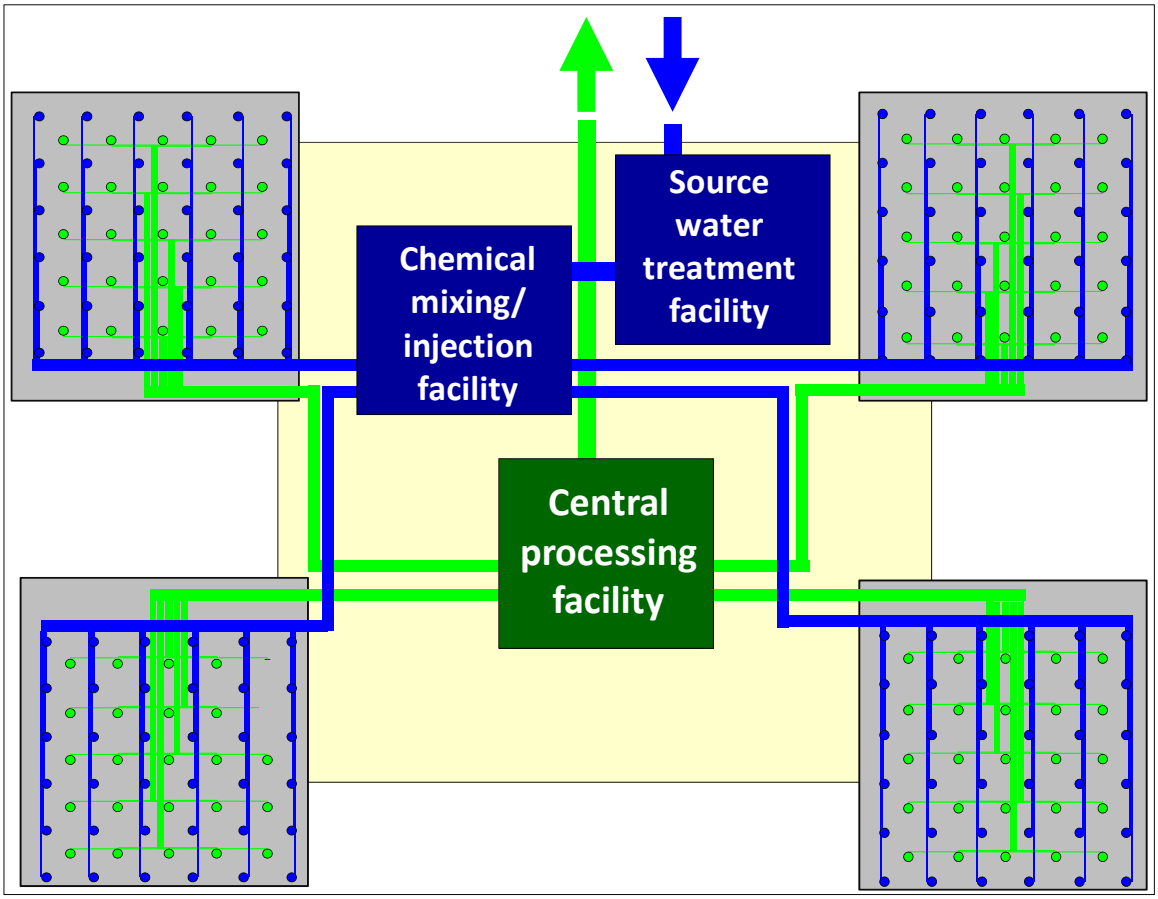

Figure 51: Upscaled layout with four 25 producer well patterns and facilities located at the center (not drawn to scale).

Reservoir dimensions and fluid volumes

Field and reservoir dimensions and volumes for the upscaled model are shown in Table 22. Many of the reservoir parameters are the same as for the benchmark model, shown in Table 4; however, the volume and well count are upscaled by a factor of 100 / 9 (i.e. 100 producers and/or 5-spot patterns now rather than 9). As used previously, the well spacing is 354 m between producers, and the five-spot area is 0.123 km^2. For 100 five-spot patterns, the total field area is 12.33 km^2, and the total STOIIP is 90.56 MMSTB.

Just as done previously, the gas-oil-ratio (GOR) is not considered in this study; gas volumes may be sufficient for separate processing facilities, compression, and sale, but this is left for more detailed study beyond reservoir-to-market screening.

Many of the simplistic reservoir modeling details will remain the same for the upscaled model as done in the benchmark model. For simplicity, this basic model will not account for volume replacement in the reservoir, or sourcing and migration parameters. Only the basic volumetric parameters described will be used, and oil will be the main fluid with water as subsidiary. This simplicity is reasonable because oil volume depletion and water/chemical injection and depletion are modeled using production type curves, and therefore, for example, the total oil volume and/or reservoir fluid volume merely acts as an upper bound constraint not actually exceeded in the model (as discussed previously). However, because the well performance type curves have such a large influence, the analogue and/or field data used in the model must be reasonable and representative.

Table 22: Field area, reservoir dimensions and volumetrics, and fluid properties for the upscaled model (derived from Table 4; Hongfu et al., 2003).

ITEM	CENTRAL WELL AREA (within 5-spot patterns)
Area and well info	
Total Area, km2	12.33
Number of 5-spot patterns	100
Area per 5-spot pattern, m2 (approx. avg)	123,333
Well spacing, m (between producers)	354
Total injectors to producers ratio	1.21
Reservoir volumes/properties	
Avg sandstone thickness, m	9.9
Avg effective thickness, m	7.1
Avg porosity, %	25
Avg permeability, md	408.7
Pore volume, MM res bbl	137.8
Initial oil saturation, %	72.3
Oil FVF	1.1
STOIIP, MMbbl	90.56

Well performance

The same well performance type curves shown in Figure 21 (as well as Figure 22) for the benchmark model were used to define the injector and producer flow rates and flooding periods for the upscaled model. However, the type curves were extended for at least an additional 10 years to evaluate the long-term financial performance of the upscaled model. For this study, the economic limit was defined where the cumulative discounted cash flow of the development project no longer increases.

Figure 52 shows the injection and production well type curves and flooding periods from Figure 22, with the type curves extended from years 12 to 22 (represented with dotted lines), and where the extended period represents the continuation of the final waterflood. The injection and production water rates are assumed to be constant during

this period, at a rate identical to the final rate in the original type curve data. The production oil rate is assumed to decline following an exponential decline using several of the later type curve data points. The oil rate equation is as such (for years 12 to 22):

$$Oil\ Rate[bbl/d] = 134.9e^{-0.154*Time[years]}$$

Because the oil rate ultimately declines to near zero, there will eventually be a point where oil revenue no longer exceeds costs, and the cumulative discounted cash flow no longer increases. This point is usually known as the economic limit, where a project at a particular point in time going forward is no longer profitable. At this point, the project should be abandoned. Another way to describe the economic limit is with the marginal cumulative discounted cash flow, which is the rate of change of cumulative discounted cash flow at a particular time. When the marginal cumulative discounted cash flow becomes negative, the economic limit is reached.

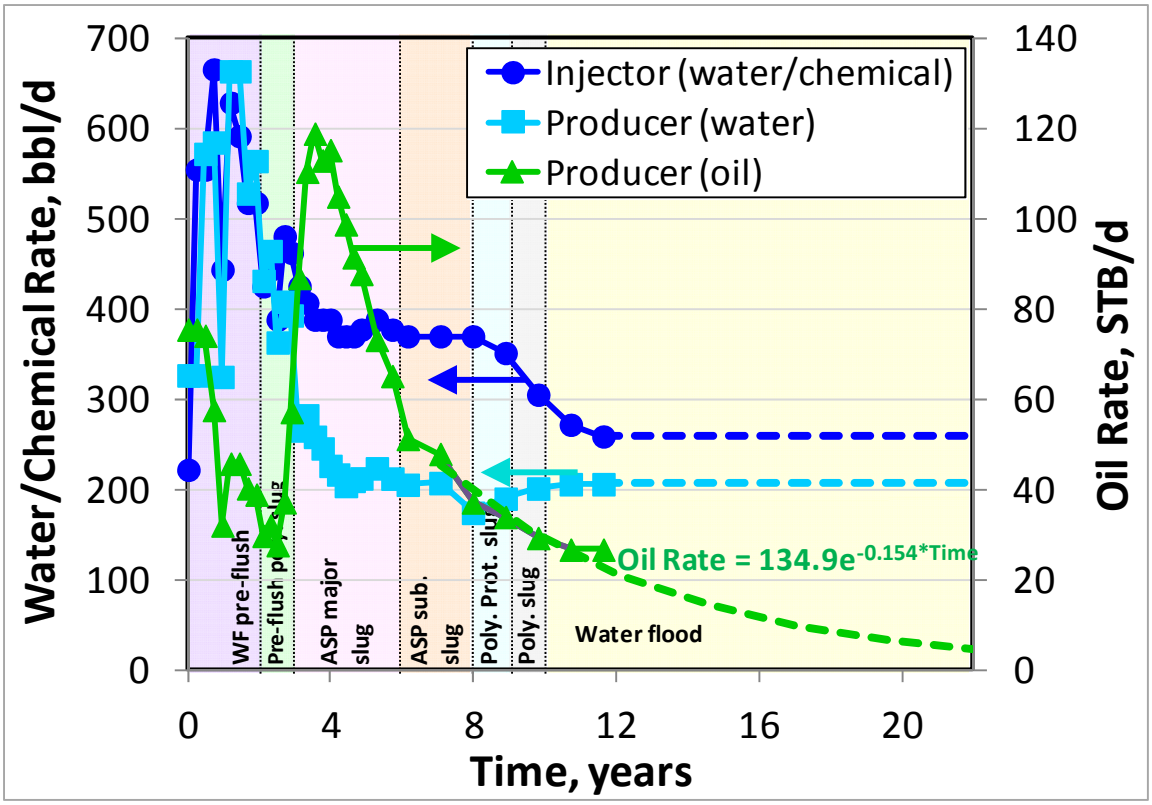

Figure 52: Injector and producer type curves for the upscaled model; flooding periods are shown, along with predicted oil rate decline.

SURFACE FACILITIES, PIPES, AND RIGS

The surface facilities described in the upscaled model are: source water treatment plant, chemical mixing and injection plant, and production fluids processing plant. The layout and connections of the main surface facilities in PetroVR was based on the process schematic shown previously in Figure 23. Each of the items represented in PetroVR, their connections, and the fluids transferring between them were specifically defined by various inputs (costs, scheduling, constraints, etc.).

One additional surface facility input considered in the upscaled model was artificial lift systems on the production wells. These were installed with the construction

of the well pad, and contained a Capex of $140,000 each, fixed Opex of $30,000 per year (approx. 20% of Capex), and variable Opex of $0.50 per barrel of fluid (power requirement for lifting).

Existing pipes connecting injector and producer wells were used in the field, and the costs of any additional pipe connections to facilities was assumed to be part of the facilities costs. Although existing wells were used, workovers to replace all the well tubing was included. The cost of the completions rig used in the workover was lumped in with the cost of the workover. A chemical EOR project in a mature field undergoing a water flood can use existing wells, and will therefore not require rigs other than performing scheduled workovers.

COSTS AND SCHEDULING

The wells, facilities, and materials costs and schedules inputs used in the reservoir-to-market benchmark model will be used for the upscaled model. This section will detail the specific cost and/or schedule information used for: facilities, wells and workovers, chemicals, and injection.

Facilities and costs and scheduling

Facilities costs used in the benchmark model will be used in the upscaled model. Table 23 lists the various items, which include: source water treatment facility, chemical mixing and injection facility, and production fluids central processing facility.

A reasonable, likely conservative assumption for each facility is a design and construction time period of 365 days and a fixed Opex value 3% of Capex per year. All the facilities are designed and constructed concurrently, and therefore 365 days would essentially be the total length of time for facilities to be operational. Although some of

the facilities may be standard “off the shelf,” the entire process of creating a basis for design, tendering, purchase and delivery, and installation could take about a year.

The ASP chemical mixing and injection facility was designed in the benchmark model for 12,000 bbl/d for 17 injector wells at a cost of $8 million. The upscaled model will contain 121 wells with identical type curves for each well. Facilities will scale up by an exponent on 0.8, meaning that if rate capacity requirements double, then the cost increases by $2^{0.8}$ times, or 1.74. For example, the chemical mixing and injection facility needs to be scaled up in capacity by a factor of 121 / 17 = 7.12. The facility cost will therefore be scaled up by a factor of $7.12^{0.8}$ = 4.8, increasing the costs to $38.5 million. The rate capacity of the upscaled facility is 85,500 bbl/d. The variable Opex for running the facility will be unchanged at $0.05/bbl to account for power requirements and other minor expenses.

The production fluids central processing facility will scale by a 0.8 exponent as well. Increasing the producers from 9 to 100 gives a ratio of 100 / 9 = 11.11, and a scale factor of 6.86. The benchmark cost and capacity was $8 million and 6,000 bbl water/d and 1,000 STB oil/d, respectively, with an Opex of $0.50/bbl for any fluid or mixture (i.e. oil, water, emulsion, etc.). The upscaled facility will cost $54.9 million for 66,700 bbl water/d and 11,100 STB oil/d capacity.

The source water treatment facility will by a 0.8 exponent with the injectors. As mentioned above, injectors will increase by a factor of 121 / 17 = 7.12, and therefore the scale factor will be 4.8. The benchmark model’s $4 million Capex and 12,000 bbl water/d scales to $19.2 million Capex and 85,500 bbl/d. The fixed Opex of 3% Capex per year (e.g. routine maintenance, repairs, inspections), and variable Opex of $0.05/bbl for facility operation (e.g. power requirements) and $1/bbl for the source water itself (e.g. water treatment) will remain the same.

Table 23: Estimated facilities costs for the upscaled reservoir-to-market model.

ITEM	VALUE
Facilities info	
Source water treatment facility	
Design/Construction time, days	365
Capex, $MM	19.3
Fixed Opex, %Capex/yr	3%
Water/injection capacity, Mbbl/d	85.5
Water Opex, $/bbl	0.05
Chemical mixing/injection facility	
Design/Construction time, days	365
Capex, $MM	38.5
Fixed Opex, %Capex/yr	3%
Water/injection capacity, Mbbl/d	85.5
Water Opex, $/bbl	0.05
Central production processing facility	
Design/Construction time, days	365
Capex, $MM	54.9
Fixed Opex, %Capex/yr	3%
Oil capacity, Mbbl/d	11.1
Water capacity, Mbbl/d	66.7
Fluids Opex, $/bbl	0.5

Well costs and scheduling

The costs, scheduling, and other information for the wells, artificial lift, and rigs are in Table 24. There are a total of 221 wells (100 producers and 121 injectors), which are existing wells. Well recompletions will cost $0.15 million Capex, and a fixed Opex of 3% of Capex per year is used. There will be one well per pad, and each well pad will have a small fixed Opex of about $1000 per year, which is negligible. Artificial lift

facilities will be installed with the well pad at a Capex of $140,000 each, fixed Opex of $30,000 per year each, and variable Opex of $0.50 per barrel (energy for lifting).

Table 24: Estimated well, artificial lift, and rig costs and other information for the upscaled reservoir-to-market model.

ITEM	VALUE
Well info	
Injectors	121
Producers	100
Well drilling/completion time, days	30
Existing well workover Capex, $MM	0.15
Well Opex, $k/yr/well	24
Well pad	
Design/Construction time, days	30
Wells/pad	1
Capex, $MM	0.03
Fixed Opex, %Capex/yr	3%
Artificial lift - sucker rod pump	
Design/Construction time, days	30
Producer wells/unit	1
Capex, $MM	0.14
Fixed Opex, $k/yr	30
Variable Opex, $/bbl	0.5

Chemical costs

Injection water and chemical costs per unit will be identical to the benchmark model with the four main items being alkali, surfactant, polymer, and source water. Just as in the benchmark model, the source water cost assumes supply (trucking, on-site water

well, etc.) and treatment (e.g. source water treatment facility) costs, and other minor chemical costs for injection and production surface facilities (biocide, oxygen and iron scavengers, demulsifiers, de-foamers, etc.) are assumed part of the general facilities operating and treatment costs. Table 25 shows the chemical costs used in the upscaled reservoir-to-market model, which are identical to those used in the benchmark model.

Table 25: Estimated chemical costs for the upscaled reservoir-to-market model.

ITEM	VALUE
Chemicals, fluids	**Cost**
Alkali, $/lb	0.22
Surfactant, $/lb	1.85
Polymer, $/lb	1.2
Water treatment, $/bbl	0.2

Injection schedule

The same injection schedule used in the benchmark model will be used in the upscaled model. Table 28 lists the injection schedule, or flooding sequence, and the respective material items and unit cost used in each stage. The only difference will be a waterflood period at the end of the flood of indefinite time length, which allows producer wells to flow an increasingly higher watercut until an economic limit has been reached. The economic limit is generally reached when the cumulative discounted cash flow curve no longer increases. At this point in time, the project is abandoned at an abandonment cost of 10% total Capex.

Although the injection schedule was the same for the benchmark and upscaled models, the injected pore volumes were different, which ultimately has an economic

effect on the chemical and injection water costs. The injector-to-producer ratio was 17 / 9 for the benchmark model, which was about 50% higher than the 121 / 100 ratio used in the upscaled model. Therefore, about 50% more fluid had to be injected per producer for the benchmark compared to the upscaled model. Table 27 compares the injected pore volumes for each injection period for the benchmark and upscaled models. As expected, the benchmark model has pore volume slugs about 50% higher than the upscaled model. This highlights one of the advantages of upscaling to a commercial scale with respect to efficient usage of injection slugs to reservoir volumes of interest.

Table 26: Injection schedule and sequence with respective material items and undiscounted costs per barrel injected for each flooding sequence for the upscaled model.

ITEM	TIME	
	AMOUNT/CONC.	COST ($/bbl)
Water flood pre-flush	**Year 0-2; 0.34 PV**	
Water	1 bbl	0
TOTAL	**1 bbl**	**0**
Pre-flush polymer slug	**Year 2-3; 0.15 PV**	
Polymer	1400 mg/L	0.59
Water	1 bbl	0.20
TOTAL	**1 bbl**	**0.79**
ASP major slug	**Year 3-6; 0.37 PV**	
Alkali	1 wt%	0.77
Surfactant	0.2 wt%	1.30
Polymer	1650 mg/L	0.70
Water	1 bbl	0.20
TOTAL	**1 bbl**	**2.96**
ASP subsidiary slug	**Year 6-8; 0.25 PV**	
Alkali	1 wt%	0.77
Surfactant	0.1 wt%	0.65
Polymer	1500 mg/L	0.63
Water	1 bbl	0.20
TOTAL	**1 bbl**	**2.25**
Polymer protective slug	**Year 8-9; 0.11 PV**	
Polymer	1000 mg/L	0.42
Water	1 bbl	0.20
TOTAL	**1 bbl**	**0.62**
Polymer slug	**Year 9-10; 0.11 PV**	
Polymer	630 mg/L	0.27
Water	1 bbl	0.20
TOTAL	**1 bbl**	**0.47**
Water flood	**Year 10-finish; 1.01 PV**	
Water	1 bbl	0
TOTAL	**1 bbl**	**0**

Table 27: Comparison of flood time and injected pore volumes (in total 5-spot pattern area) between the pilot and upscaled models.

FLOOD PERIOD	PILOT		UPSCALED	
	Time (yrs)	Pore Vol. Inj.	Time (yrs)	Pore Vol. Inj.
Water flood pre-flush	2	0.53	2	0.34
Pre-flush polymer slug	1	0.23	1	0.15
ASP major slug	3	0.59	3	0.37
ASP subsidiary slug	2	0.36	2	0.25
Polymer protective slug	1	0.20	1	0.11
Polymer slug	1	0.15	1	0.11
Water flood	1.5	0.24	9.4	1.01

OTHER ECONOMIC INPUTS (OIL PRICE, TAXES, DEPRECIATION, ETC.)

Many of the other economic input parameters besides Capex and Opex were the same in the upscaled model as the benchmark model. These item categories include oil price, depreciation, and taxes/royalty parameters, which are shown in Table 28. The upscaled model was tested using a flat crude oil price of $100/STB oil, as well as the MR price models generated in Chapter 4. For simplicity, neither API and sulfur content quality correction nor price inflation was used for the crude oil. Additionally, cost inflation over time for Capex and Opex items was not considered. Regarding depreciation, all Capex items start depreciation as they are built, and they are depreciated using the straight line method over a 10 year period (with no salvage value). The federal and state income tax rates are assumed to be 35% and 5%, respectively, while the royalty and severance ad valorem are assumed to be 10% and 5%, respectively. The discount rate used for NPV calculations is assumed to be 5%.

Table 28: Economic inputs for the upscaled model, including oil price, inflation, depreciation, and tax information.

ITEM	VALUE
Oil price, quality, and price/cost inflation	
Crude oil price	
Base case, $/bbl	100
Oil price modelling, $/bbl/month	MR price model
Depreciation	
Depreciation period, years	10
Depreciation method	Straight Line
Salvage value, $	0
Start time	As Built
Depreciable items	All Capex
Taxes, royalities	
Federal income tax, %/yr	35
State income tax, %/yr	5
Royalty, %/yr	10
Severance ad valorem, %/yr	5
Discount rate, %/yr	5

UPSCALED RESERVOIR-TO-MARKET MODEL OUTPUT

All of the inputs described in the previous sections were inputted into the upscaled reservoir-to-market model, and the model was run and results were generated. This effort was relatively straightforward because many of the input parameters and layout already existed in the benchmark model. The relevant simulation output for project valuation was production and injection forecasts, and cash flow calculations and economic metrics.

PRODUCTION AND INJECTION FORECASTING RESULTS

Production and injection forecasting results generated by the PetroVR model should match the inputted type curve performances, subject to various constraints (e.g. facilities capacity). In this model, facilities were planned to accommodate more than the maximum expected fluid injection and production, and there were therefore no constraints. Figure 53 shows the total injection and production rates of all wells combined over the project life. These output curves are subject to the inputted type curves provided for each well, and therefore the well production follows the inputted type curves with relatively little constraint.

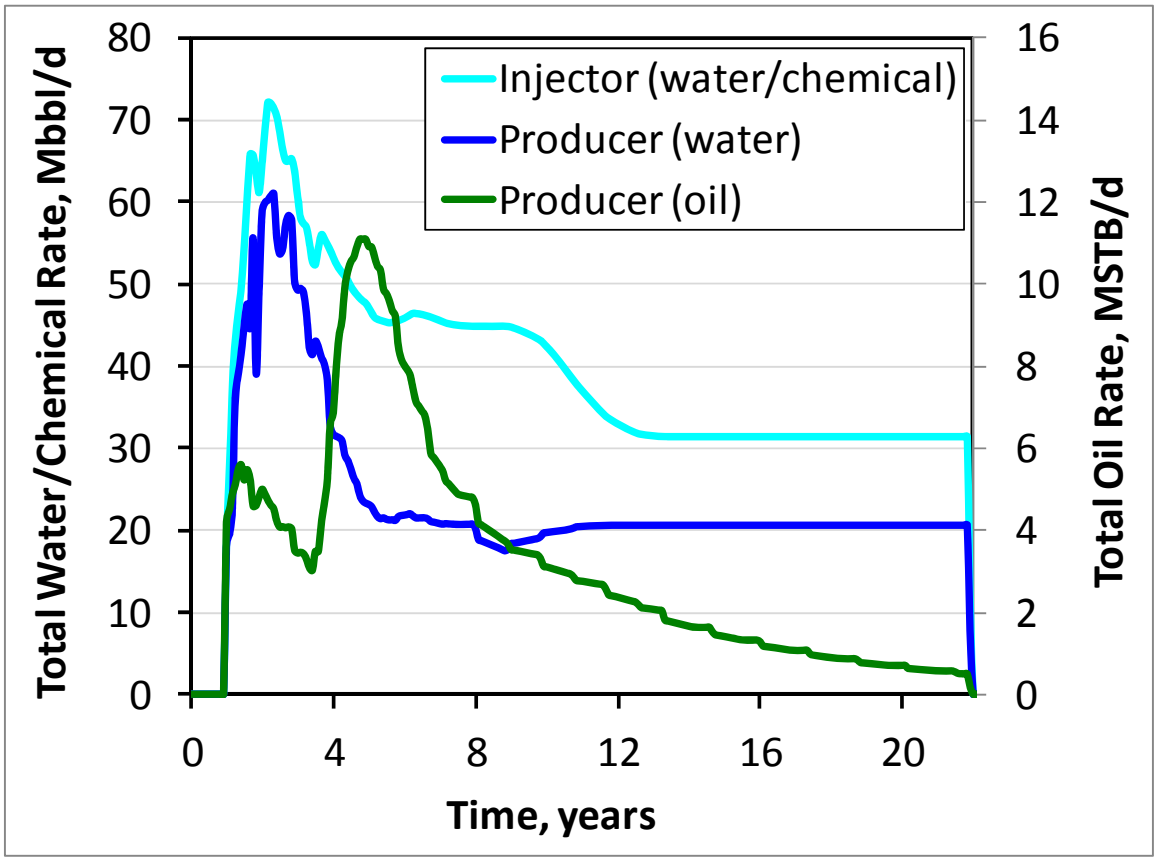

Figure 53: Forecast results for injection and production generated by the PetroVR upscaled model.

ECONOMIC RESULTS AND METRICS

Economic output data and analyses typical to business financials and accounting include: revenue, royalty, severance, Capex, Opex, earnings before taxes, loss carry forward, taxable income, federal and state income tax, cash flow, and economic metrics (NPV, IRR, UTC, VIR, and payback period). Most of the data shown in this section is undiscounted, except for the discounted cash flow and economic metrics.

Revenue, Royalty, and Severance

The total revenue, royalty, and severance tax results generated by the reservoir-to-market model are in Figure 54. The oil price, royalty, and severance tax values used in the economic analysis are in Table 28. Both the revenue and royalty plus severance curves trend the oil production curve because oil production is ultimately what drives the monetary inflows and tax outflows during the project.

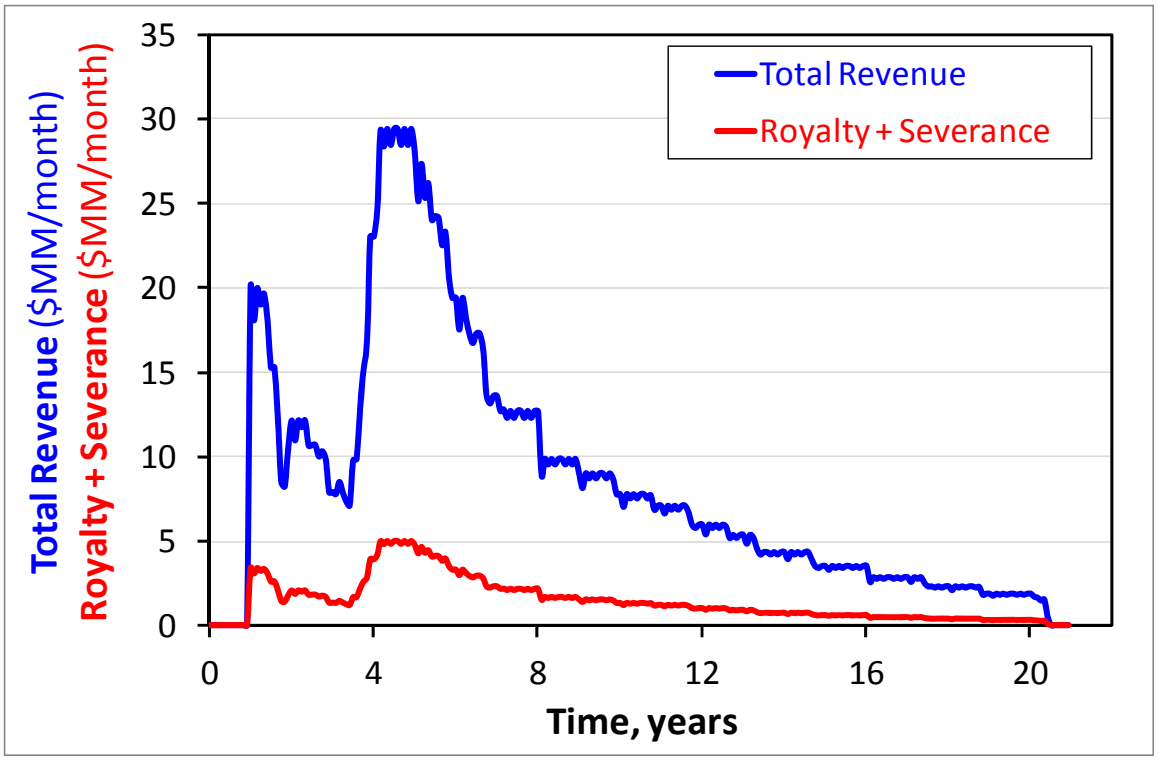

Figure 54: Total revenue, royalty, and severance tax results generated by the reservoir-to-market upscaled model.

Expenses – Opex, Capex, and Depreciation

The various expenses generated by the reservoir-to-market model, including total Capex, total Opex, and depreciation, are shown in Figure 55. Most of the Capex is accrued during the first couple of years when the facilities and wells are being developed. The spike at the end is the abandonment cost (i.e. 10% of the total Capex items). The total Opex curve accounts for all the fixed Opex associated with the facilities and wells, as well as the variable Opex from the chemical flooding materials and fluids treatment (source water, injection fluids, and production fluids). The depreciation curve was generated using the straight-line depreciation method, which depreciates the Capex costs accrued during the first year over a 10-year depreciation period. The abandonment Capex

item at the end of the project life cannot be depreciated as the project completes at that time. Values are undiscounted in this plot as well.

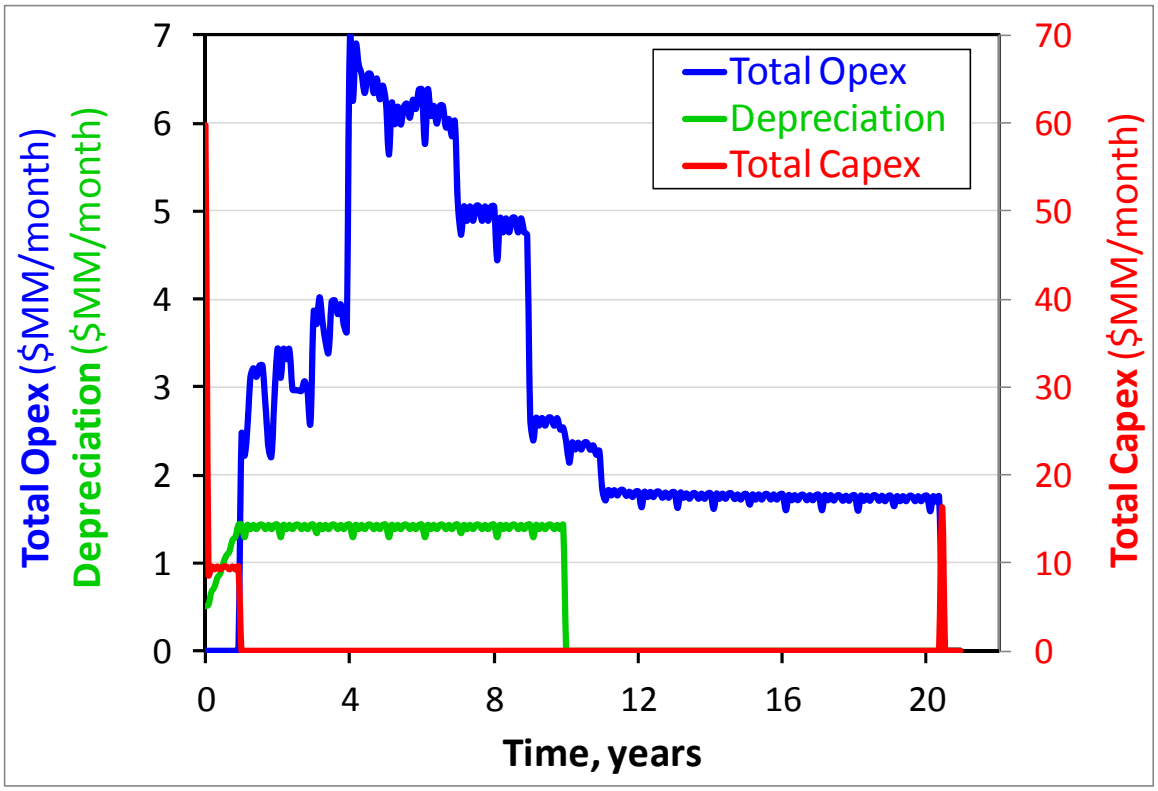

Figure 55: Total Opex, Capex, and depreciation results generated by the reservoir-to-market upscaled model.

Earnings before Taxes, Loss Carry Forward, and Taxable Income

The earnings before taxes and loss carry forward numbers calculated by the reservoir-to-market model are in Figure 56, which also includes a curve of their summation. The net earnings before tax curve represents the value calculated for a given month; it is simply the revenue minus the Opex minus the depreciation for that month. The loss carry forward represents the cumulative losses during the project that have not

been offset by positive net revenue. Carrying losses forward can offset some or all of the income for a particular time period at which income taxes need not be paid, as income tax is paid only on net gains, not net loses. The cumulative net earnings before taxes and the loss carry forward are useful in determining taxable income. Income taxes are only taken out if net earnings before taxes are positive. Therefore, a taxable income plot is identical to the net earnings before taxes plot between years 1 and 20 (Figure 57).

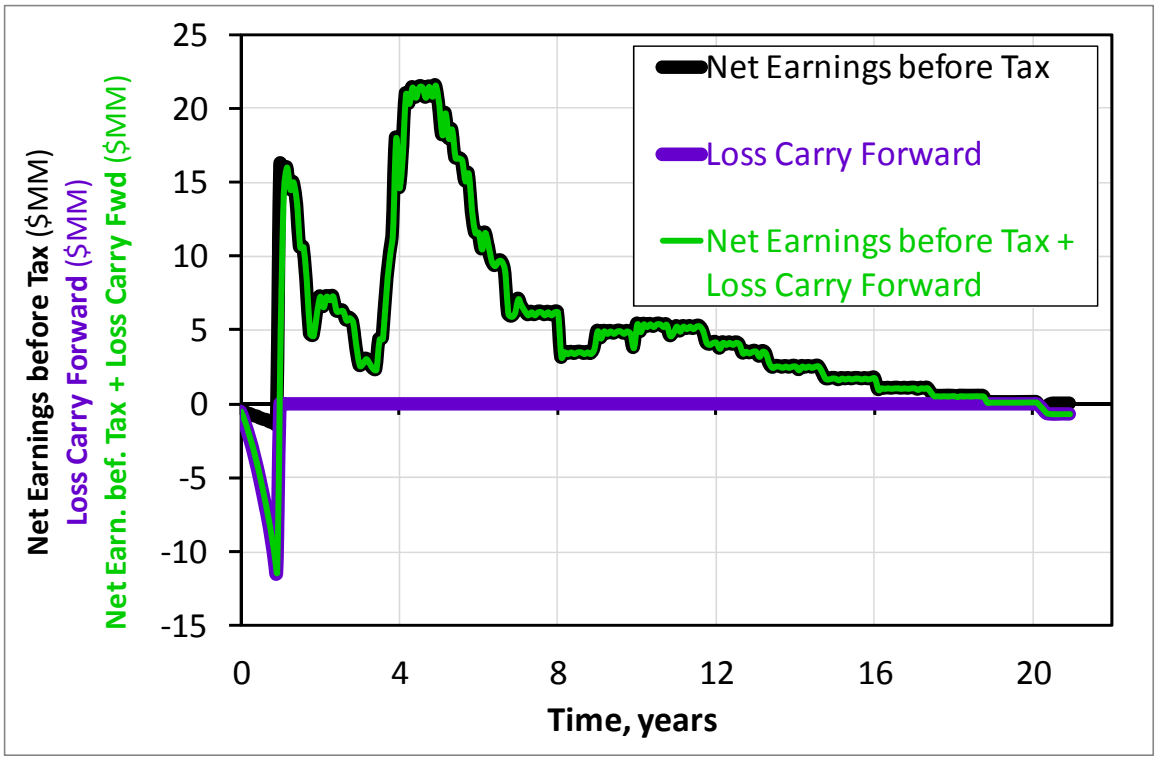

Figure 56: Net earnings before tax, loss carry forward, and their summation results generated by the reservoir-to-market upscaled model.

Taxable income, and federal and state income taxes

Figure 57 shows the taxable income along with federal and state income taxes. The federal and state income tax rates were 35% and 5%, respectively, and therefore the respective tax curves are essentially scaled down versions of the taxable income curve. Income taxes are one component that subtracts from revenue to give after tax cash flow.

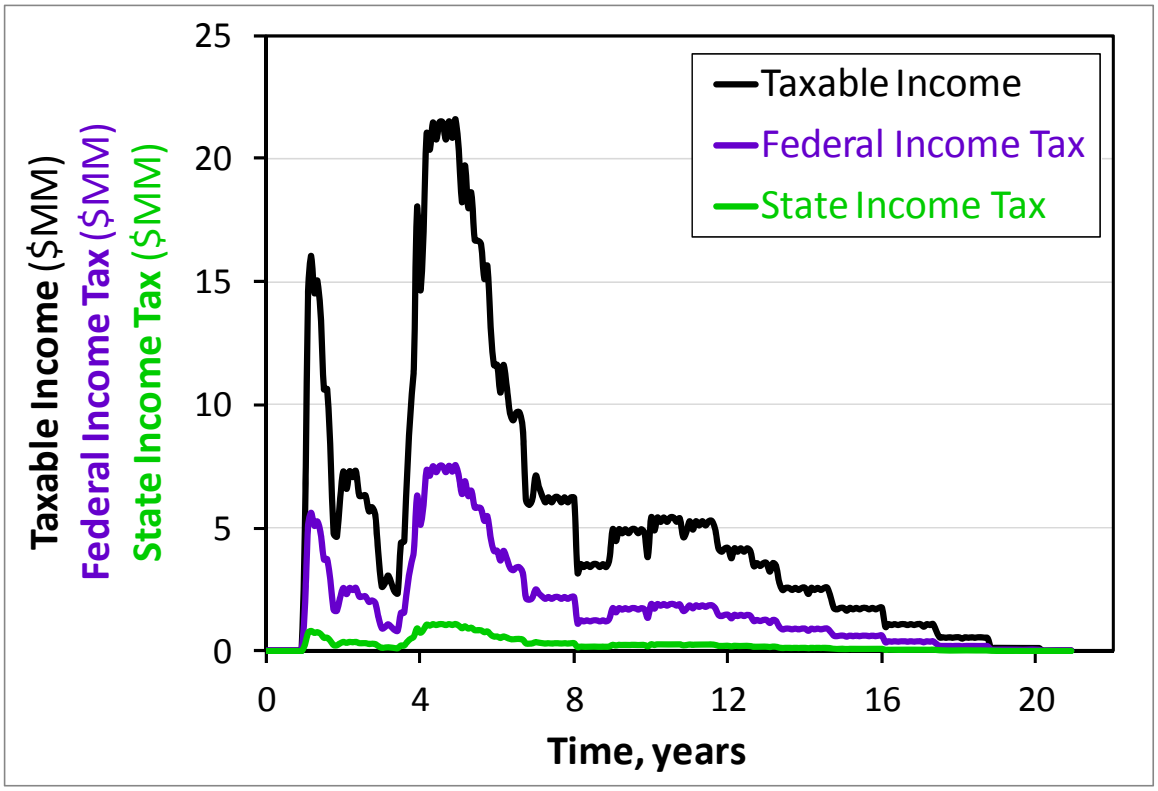

Figure 57: Taxable income and federal and state income tax results generated by the reservoir-to-market upscaled model.

Cash Flow

The monthly cash flows and NPV of cumulative discounted cash flow (using 5% discount rate) over the project life are in Figure 58. The monthly cash flow after tax is the

revenue minus royalty and severance minus Capex and Opex minus income tax for a given month. Capex has the largest effect on cumulative discounted cash flow during the first couple of years, and after that cash flows are almost always positive throughout the project life. The abandonment cost at the end of the project is approximately $17 million. The cumulative discounted cash flow curve is negative until about 3.3 years (which is the payback period).

The cumulative discounted cash flow curve in Figure 58 shows a flattening around 20 years, after which the cumulative discounted cash flow would begin to decrease with time. This is because monthly cash flows will become negative, causing the cumulative discounted cash flow curve to decline. To optimize project NPV, projects are generally discontinued when cash flow (e.g. monthly) becomes negative, and this point can be thought of as an economic limit. In this upscaled model, the project is abandoned at the point where monthly cash flow after tax is approximately equal to zero.

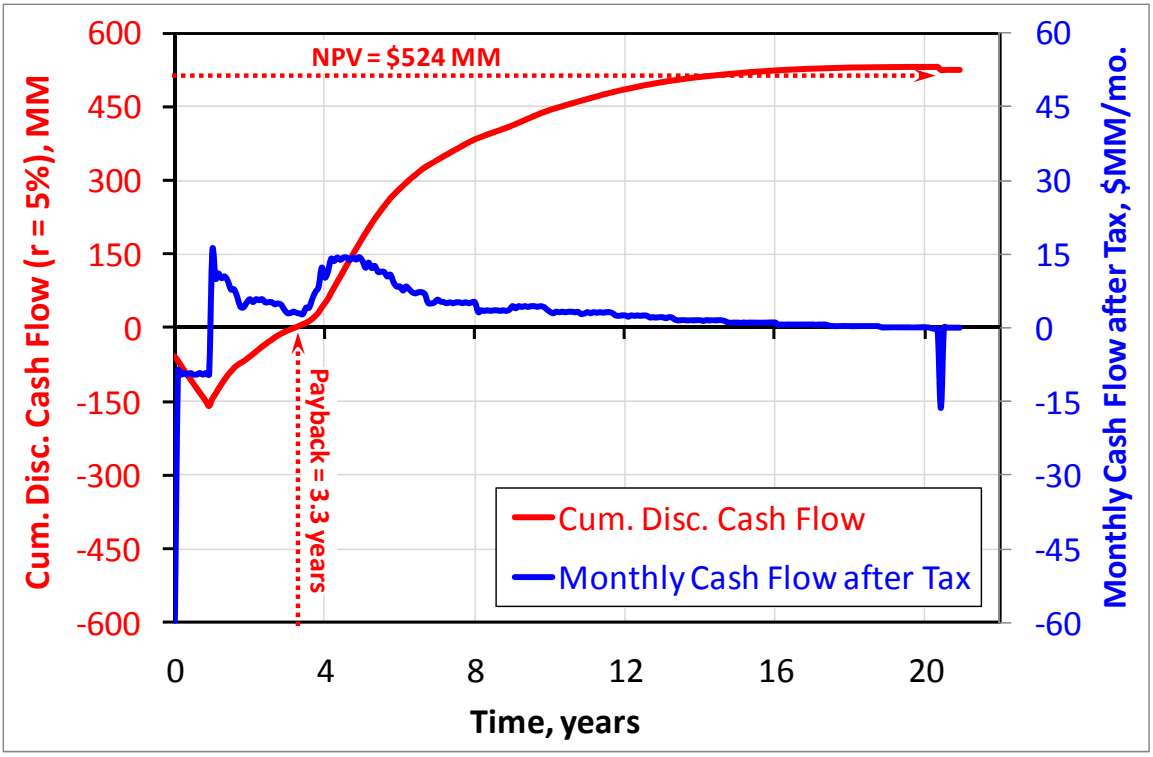

Figure 58: Upscaled model results for cumulative discounted cash flow and monthly cash flow; project ceases when monthly cash flow equals zero.

Economic Metrics (NPV, IRR, UTC, VIR, and Payback Period) and other results

Simple economic metrics can give an idea of a project's valuation, and these metrics include: NPV, IRR, UTC, VIR, and payback period. Table 29 lists these economic metrics and other results for the reservoir-to-market upscaled model. The NPV calculated at a 5% discount rate was $524 million, indicating a positive NPV. The IRR was 52.5%, meaning that if a discount rate less than 52.5% was used, the NPV would be positive. Figure 59 shows an NPV versus discount rate curve, which crosses the x-axis at the IRR value of 52.5%.

The undiscounted UTC was calculated to be $33.81/STB, which is less than the benchmark model undiscounted UTC around $42.79/STB. The discounted UTC using a

5% discount rate was $30.80 per discounted stock tank barrel. The VIR was calculated to be 3.9, which is greater than one, and therefore the project NPV is greater than the initial investment. The payback period was 3.3 years. Other results in Table 29 show total undiscounted oil production of 25.5 MMSTB. Additionally, the maximum cash out during the project was -$160 million, the total royalty was $243 million, total severance was $122 million, total federal income tax was $447 million, and total state income tax was 63.9 million.

Table 29: Economic metrics and other results generated from the reservoir-to-market upscaled model.

ITEM	VALUE
Economic Metrics	
Net Present Value (NPV) at 5% discount rate, $MM	524
Internal Rate of Return (IRR), %	52.5%
Unit technical cost (UTC) undiscounted, $/bbl oil	33.81
Value to Investment Ratio, VIR	3.9
Payback Period, years	3.3
Other Results, undiscounted	
Total Oil Produced, MMbbl	25.5
Maximum Cash Out, $MM	-160
Total Royalties, $MM	243
Total Severance, $MM	122
Total Federal Income Tax, $MM	447
Total State Income Tax, $MM	63.9

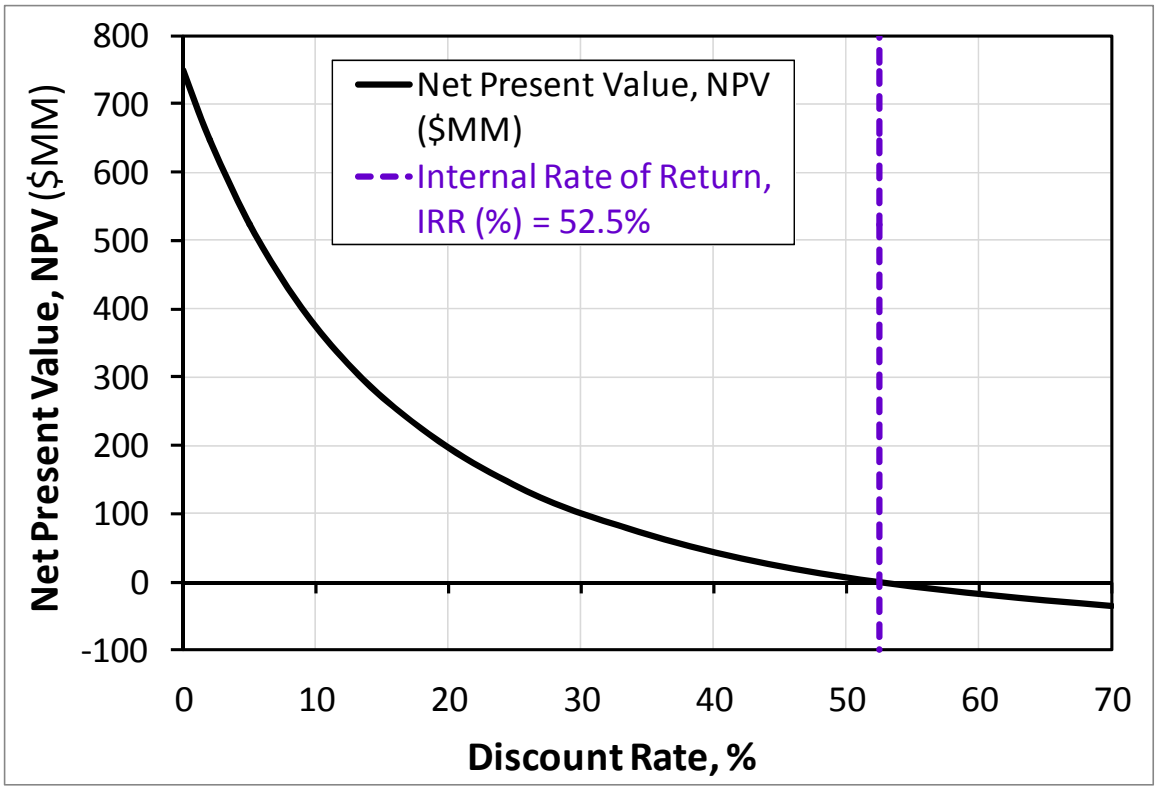

Figure 59: NPV versus discount rate with IRR displayed calculated from the reservoir-to-market upscaled model results.

Costs and cost per barrel oil produced

Table 30 shows input parameter item cost using discount rates of 0% and 5%. Similarly, shows input parameter category costs using 0% and 5% discount rates as well. The total costs over the life of the project are about $861 million and $558 million for 0% and 5% discount rates, respectively. Although cost items with more Opex than Capex may not necessarily be discounted more simply because Opex occurs throughout the project life, as Capex is depreciated over the project life as well. Table 31 shows the undiscounted and discounted cost breakdown of input parameters and categories on a $/bbl oil produced basis. Chemical and treated water inputs account for about 30% of

costs, which is less than the 40% calculated in the benchmark model. The discounted costs per barrel oil produced used discounted barrels in the calculation.

Table 30: Cost breakdown of input parameters and categories on a total cost basis, both undiscounted and discounted.

ITEM	COST, $MM	
	Undiscount.	5% disc. rate
By Input Parameter		
Produced fluids processing (Opex)	233.97	123.60
Wells, well pad, pump jacks (Opex)	163.28	72.80
Surfactant	86.97	64.87
Polymer	77.18	56.83
Chemical mixing/injection facility	75.65	55.48
Alkali	64.31	47.13
Central production processing facility (Capex)	54.87	53.66
Source water treatment facility	44.91	31.46
Existing well tubing (Capex)	33.15	33.15
Water treatment	26.26	19.02
TOTAL	**860.55**	**558.00**
By Category		
Facilities	409.40	264.20
Chem/Inj. Water	254.73	187.85
Wells	196.43	105.95
TOTAL	**860.55**	**558.00**

Table 31: Cost breakdown of input parameters and categories on a cost per barrel of oil produced basis, both undiscounted and discounted.

ITEM	COST, $/bbl oil	
	Undiscount.	5% disc. rate
By Input Parameter		
Produced fluids processing (Opex)	9.19	6.82
Wells, well pad, pump jacks (Opex)	6.42	4.02
Surfactant	3.42	3.58
Polymer	3.03	3.14
Chemical mixing/injection facility	2.97	3.06
Alkali	2.53	2.60
Central production processing facility (Capex)	2.16	2.96
Source water treatment facility	1.76	1.74
Existing well tubing (Capex)	1.30	1.83
Water treatment	1.03	1.05
TOTAL	**33.81**	**30.80**
By Category		
Facilities	16.09	14.58
Chem/Inj. Water	10.01	10.37
Wells	7.72	5.85
TOTAL	**33.81**	**30.80**

Effect of MR Oil Price Models on Project Economics

Oil price fluctuations can have an extremely large effect on overall project economics and valuation, and often determines other project expenses as well (given that materials, transportation, and power costs among other things are generally correlated to the oil price). Figure 17 shows ten MR oil price model forecasts that were generated based on historical and futures Brent crude oil prices. These MR oil price models were used in the upscaled reservoir-to-market model with an about a 20 year lifespan to determine their effect on project valuation. The MR models shown in Figure 17 were

plotted for 15 years; however, they were run slightly longer to generate the oil price data used in the reservoir-to-market model described here. All projects were run for approximately 20 years even though portions were uneconomic, which may be true of real life scenarios. Projects can sometimes continue even when cash flow is negative because of complications in shut-down and start-up and oil price fluctuations.

Figure 60 shows that the MR oil price model causes the cumulative discounted cash flow to vary substantially over a project lifespan. Using only 10 different MR oil price models, NPV (5% discount rate) varied widely from $234 million to $923 million. The 10 MR oil price models used here cover a reasonably wide range, as shown in Chapter 4 where 10 and 100 MR price models cover a similar range. Figure 61 shows some economic metrics generated from the 10 different model runs. These metrics are plotted against the average oil price obtained from each of the 10 respective MR oil price models used in the simulations. As expected, NPV and IRR increase with oil price, while payback period decreases. As mentioned, NPV varied from $234 million to $923 million, while IRR varied from 36.7% to 70%, and payback period varied from 2.5 years to 3.9 years.

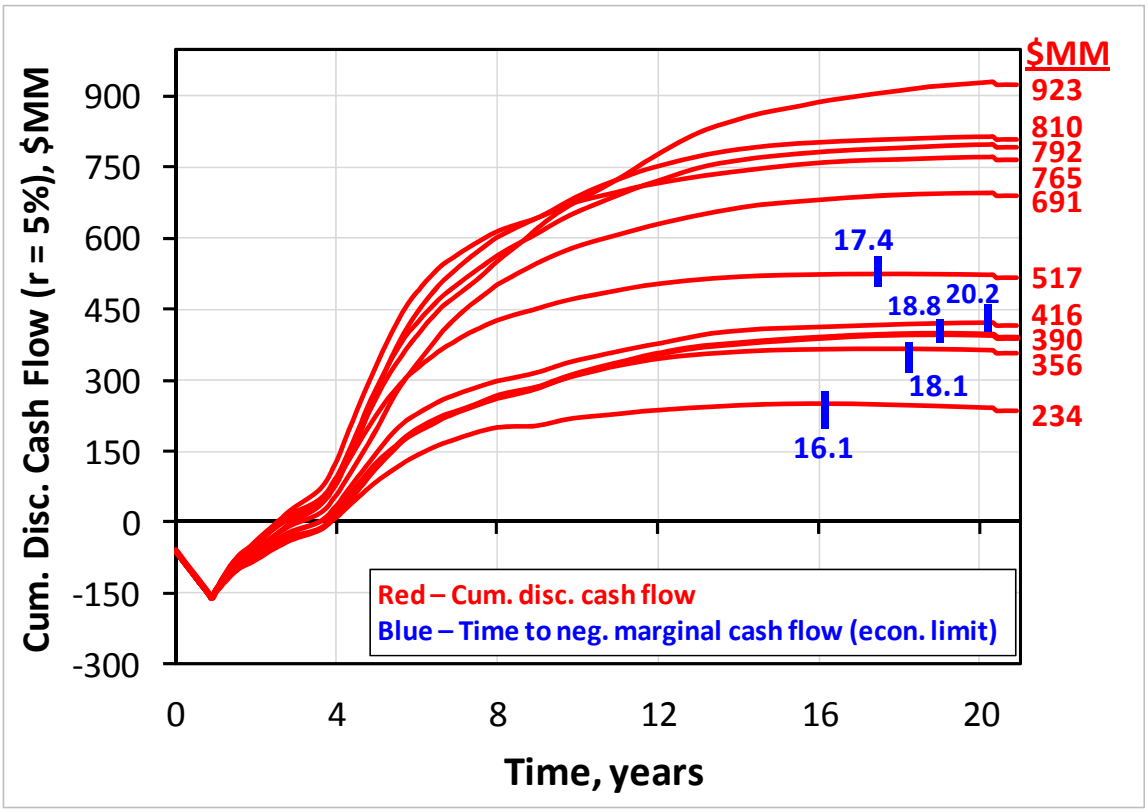

Figure 60: Upscaled model results for cumulative discounted cash flow using the ten different MR oil price models from Figure 17.

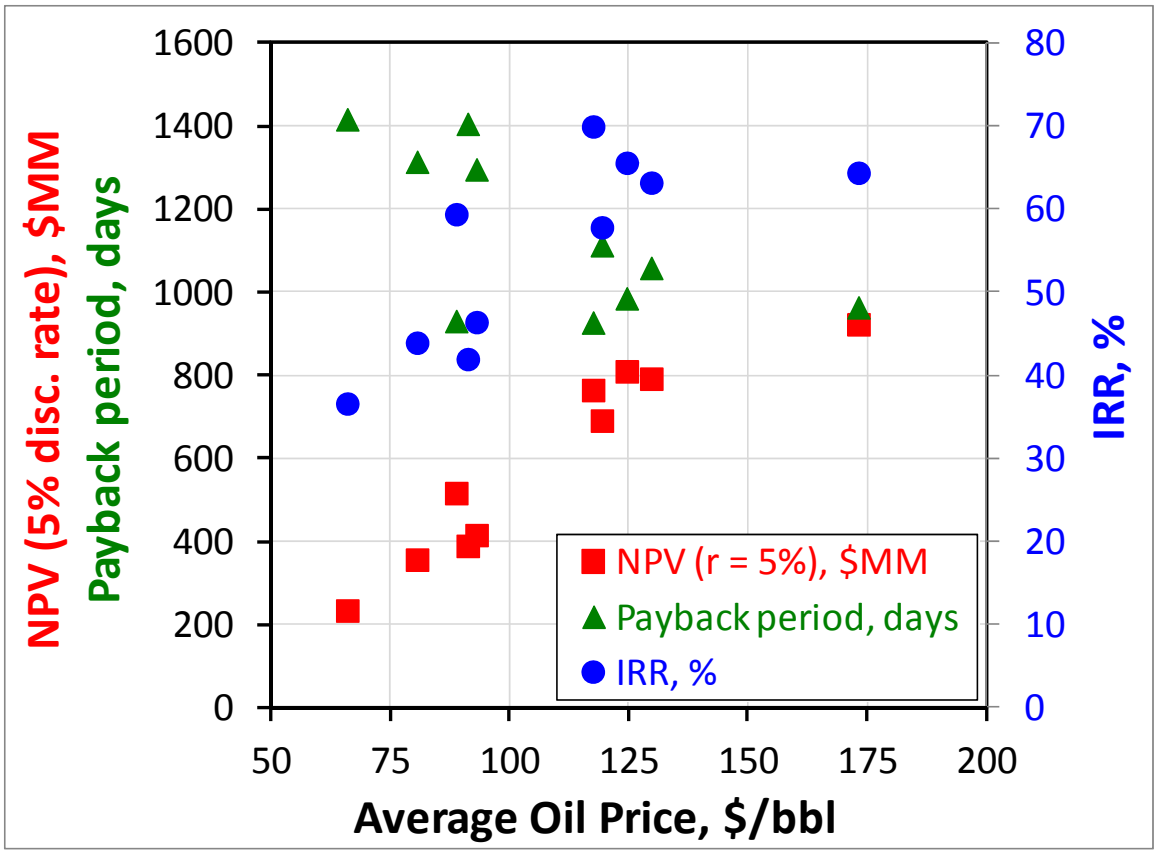

Figure 61: Economic metrics results plotted against the average oil price obtained from the MR oil price model used for the 10 upscaled simulations.

OVERALL OPPORTUNITY VALUATION

The various economic metrics calculated from the reservoir-to-market model help in valuing the commercial-scale chemical EOR opportunity. Table 29 shows the calculated economic metrics from the upscaled reservoir-to-market model, which was economically favorable. The NPV (at 5% discount rate) was positive at $524 million, IRR was 52.5%, the VIR was greater than one at 3.9, and the payback period was relatively short at 3.3 years. Based on these favorable results though, the project should continue further review, tuning, and valuation, rather than be discarded.

SUMMARY AND CONCLUSIONS

A methodology was provided for upscaling a reservoir-to-market model for purposes of valuing a commercial-scale chemical EOR opportunity. The upscaled model used the well performance data from the pilot, as the reservoir was similar but larger. Economic metrics generated for the upscaled model showed favorable results for project valuation. A few aspects of project valuation were explored, including the use of an economic limit and applying an MR oil price model. This upscaled model shows that a commercial scale chemical EOR project has a favorable NPV given the current oil price, cost inputs, and expected well performance.

Several important conclusions were made when developing the upscaled reservoir-to-market model for commercial scale project assessment. The overall economics were favorable. The NPV was $524 million using a 5% discount rate, and the IRR was 52.5%. Furthermore, the project paid back relatively quickly at 3.3 years. Even though the maximum cash out was -$160 million after the first year, due to large Capex items, these costs were recovered quickly. The project was run for approximately 20 years before being abandoned, which was the time to reach the economic limit (characterized by negative monthly cash flow).

The well layout contained an injector to producer ratio of 1.21, which corresponded to 121 injectors for 100 producers. This ratio was about 40% lower than the pilot, where 17 injectors and 9 producers were used. As a result, the chemical slug pore volumes used for injection were about 40% lower. For example, the ASP slugs were 0.62 PV, compared to 0.95 PV for the pilot. This was a key factor to decreasing the chemical costs per barrel of oil recovered.

Chemical costs accounted for more about 30% of costs per barrel oil produced, which was much less than the 40% calculated for the pilot. Facilities costs were about

45% to 50% of total cost per barrel oil produced, which is slightly more than the pilot. Facilities costs were not upscaled linearly with capacity, but by an exponent of 0.8 (i.e. $2^{0.8} = 1.74$ increase in cost with 2-fold incrase in capacity). This helped facilities costs not increase substantially as a proportion of the total cost per barrel oil compared to the pilot model. The wells costs increased to about 20% of total costs per barrel oil produced, which was substantially higher than the pilot. This is because most wells costs scaled linearly with increase in field size, so there was no big cost savings.

Of the individual costs, the produced fluids processing cost Opex was the largest, at about $7 to $9 per barrel. This is because produced fluids processing occurs during the entire length of the project, whereas other Opex items, such as chemical costs, only occur when chemical slugs are being injected. This is also highlighted by the difference in undiscounted and discounted produced fluids processing costs at $9.19 and $6.82 per barrel oil, respectively, which indicates that costs are being incurred very late in the future. Conversely, many other cost items actually increase when discounted, as they are assessed per discounted barrel of oil. Well costs were the second highest cost per barrel oil, as these too are Opex costs over the life of the field. Sufactant, polymer, and alkali costs were still the 4th, 5th, and 6th largest costs per barrel oil, respectively, even though they are incurred in the first half of the 20 year field life. This shows the significant cost of chemicals in chemical flooding. Overall, the UTC was around $30 per barrel oil produced for the upscaled model, compared to around $45 per barrel oil for the pilot model.

Oil price modeling had a significant effect on the project economics of the upscaled model. Ten different mean-reversion price model runs were each used in the upscaled model, resulting in an NPV variation from $234 million to $923 million. The average oil price of the models at each of these extreme NPV values were about $65/bbl

and $175/bbl, respectively. Also for these two extreme price models, the IRR ranged from about 36% to 70%, and the payback period from about 2.5 to 4 years. The fact that the economics are favorable for all oil price models shows the promise of a commercial scale chemical EOR project.

CHAPTER 9: SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

SUMMARY

The main objectives described in Chapter 1 were addressed in this research. A process-oriented framework was created that integrates all key project aspects for quick valuation and screening of chemical flooding opportunities early in the project development phase. The potential of a reservoir-to-market modeling approach to determine chemical EOR opportunity valuation, and ultimately project feasibility was demonstrated through the workflow, model building, and generation of economic evaluation metrics. A reservoir-to-market benchmark model was developed that can be applicable to other potential chemical EOR opportunities of similar nature. Parameters were identified that influence the chemical EOR opportunity valuation, and techniques were employed for model simplification and efficiency.

Determining key parameters that influence the chemical EOR opportunity valuation was performed based on chemical EOR case studies, as well as through sensitivity analysis and Monte Carlo simulations with the reservoir-to-market model. Production forecasting and economic evaluation techniques were also described and used in the reservoir-to-market model. A general reservoir-to-market model for chemical EOR opportunity valuation was successfully developed and produced interpretable results. The model was upscaled to assess a commercial project.

A method to understand and improve project economics towards a decision making goal was successfully demonstrated. A reservoir-to-market benchmark model for an onshore oil field was successfully built and tested, and could value projects using standard economic metrics (net present value, internal rate of return, value investment

ratio, unit technical cost, and payback period). Parameters with distribution ranges were used to model uncertainty. Model simplification was achieved through global sensitivity analysis and discretization of input parameter uncertainties. Model efficiency was achieved through discretization, which sped the screening process. Decision-making between model alternatives given information and different states of nature was performed through decision analysis techniques based on integration of scenario building, the technical understanding of EOR, and overall project valuation. Overall, the approach was novel and provided benefit as a robust, integrated process-oriented framework for early chemical EOR project screening, valuation, and decision-making.

CONCLUSIONS

Several important conclusions were obtained from the benchmark model, from sensitivity and discretization analysis based on the benchmark model, and from upscaling the benchmark model.

The overall economics were favorable for both the benchmark model of the multi-patterned pilot, and the upscaled model representing a commercial ASP flood. The NPV of the benchmark model was $32.4 million using a 5% discount rate, the IRR was 30.5%, and the payback period was 4.3 years. The upscaled model had a NPV of $524 million using a 5% discount rate, IRR of 52.5%, and payback period of 3.3 years. Even though for both projects the maximum cash out was very high in the first year (-$24.9 million and -$160 million for pilot and commercial, respectively) due to large Capex items, these costs were recovered very quickly.

The upscaled model was more economically favorable than the pilot because of the lower injector to producer ratio, which led to better confinement of injected chemicals within the well patterns, and therefore better utilization of the chemicals. The pilot

project contained 17 injector wells to 9 producers, while the upscaled model contained 121 injectors to 100 producers (nearly a 40% reduction in injector to producer ratio). As a result, cumulative pore volumes of the ASP slugs accounted for 0.95 pore volumes injected for the pilot, and 0.62 pore volumes for the upscaled model. The cost savings of chemicals was reflected in the NPV of the upscaled model. Surfactant, polymer, and alkali discounted costs were $6, 5.50, and 4.50 per discounted barrel oil produced for the pilot, and $3.50, 3, and 2.50 per barrel oil produced for the upscaled model.

Total costs per barrel of oil produced and breakdown of costs differed for the pilot and upscaled models. The pilot had a unit technical cost of $45 per barrel of oil, while the upscaled model was $30. Chemical costs accounted for 40% of the total costs for the pilot, and 30% for the upscaled model. Facilities costs were not upscaled linearly with capacity, but by an exponent of 0.8 (i.e. $2^{0.8} = 1.74$ increase in cost with 2-fold increase in capacity). This provided some facilities cost savings with upscaling. For example, the chemical injection and mixing facility cost $6.50 per barrel of oil in the pilot versus $3 per barrel oil in the upscaled model. For the upscaled model, produced fluids processing Opex was $7 per barrel.

Uncertainty of input parameters was represented by continuous normal distributions, and used for global sensitivity analysis with the Sobol method. The Sobol sensitivity analysis showed 1000 samples were necessary for convergence, where mean output NPV stabilized and variance became nearly zero. The chemical mixing and injection facility showed the highest sensitivity, followed by surfactant and polymer chemical costs. The central production processing facility and produced fluids processing are also associated with facilities costs, and showed the 4^{th} and 5^{th} highest total sensitivity, with the alkali sensitivity being sixth highest of 11 input parameters. Total sensitivity was between about 0.1 and 0.15 for each of the six input parameters showing

the highest sensitivity. Sensitivity analysis helped identify 6 parameters with the highest sensitivity that were used for discretization. The facilities and chemical costs each accounted for 40% of total sensitivity.

The discretization technique was advantageous because it reduced the number of model runs used in the Monte Carlo sampling technique. Only the 6 input parameters showing the highest sensitivity were discretized. 3-point discretization simplified the number of model runs to $3^6 = 729$ compared with 1000 to 10000 used in the Sobol method. Discretization was also demonstrated in decision-tree analysis to assess conventional and novel alkali scenarios. Novel alkali cost twice as much, but eliminated water treatment and halved the source water facilities cost. However, the novel alkali scenario had a P50 NPV of $31.7 million, lower than the NPV of $32.4 million for conventional.

Oil price has historically been very volatile. Oil price modeling using the mean-reversion price model showed a significant change in the oil price over a project lifetime. For example, average values within each of ten runs showed the average price to range from $65/bbl to $175/bbl. Sensitivity analysis showed oil price to account for 98% of the total sensitivity. Applying ten price model runs to the upscaled model showed NPV to vary from $234 million to $923 million, IRR from 36% to 70%, and payback period from 4 to 2.5 years, respectively. Oil price dominates sensitivity, which highlights the importance of fixing oil price when determining how sensitivities of other input parameters compare to one another. Also, the fact that the economics are favorable for all oil price models shows the promise of a commercial scale chemical EOR project.

There are several important qualifications and assumptions that relate to this work. These qualifications focus on the Daqing pilot in particular, general chemical EOR projects, larger financial and political factors, and the calculations used in the study.

The chemical EOR technology used in the Daqing pilot is old from the mid-1990s and there have been highly significant advances in the technology in recent years. The flood design was unconventional, including five different polymer and ASP flooding periods. Chemical floods in general contain only two chemical flooding periods, a surfactant slug and a polymer drive. The field had not been waterflooded prior to the short waterflood period that started the pilot, and was therefore not a mature field. Candidate fields for chemical flooding oftentimes have been waterflooded for decades, and show little additional oil recovery to waterflooding. Despite this, the Daqing field pilot had a low recovery factor of about 24% of initial oil. The chemical prices used in the study were representative of prices at the time of the pilot, but are lower than current prices for similar products. Also, although the Daqing pilot location was in China, the royalty, severance tax, and income tax rates are representative of the U.S. Wyatt et al. (2008) was the source of most of the other costs.

Compared to potential chemical EOR projects in general, the pilot assessed in this study is very specific, and a lot of parameters were assumed to be known. Geology and reservoir properties are highly variable and uncertain, and have a major effect on project performance. Predicted well performance is usually defined as a distribution of type curves with an uncertainty range, whereas in this study actual well rates were used. The condition and availability of surface facilities and infrastructure is variable. For instance, wells could be old or new, and facilities could be in good or poor condition. This study assumed new facilities would be needed, an existing pipe network could be used, and old wells were functional with a tubing replacement. However, other fields will have different infrastructure and related costs.

Financial, economic, and political assumptions were also made, which will differ depending on project location and time period. A discount rate of 5% was assumed,

which may be reasonable at the current time, but is historically low. State tax and severance tax were each assumed to be 5%; however, in some states they could be zero or nearly zero, which would have a large impact on economics (nearly $10 per barrel of oil). Tax rates could change or tax incentives could be given for EOR.

The uncertainty ranges used in the sensitivity study were assumed to be normal distributions with a small standard deviation of 10% of the mean, which is small compared to some projects. Projects screened early in development will have costs that are much more uncertain. Uncertainties are not always normal continuous distributions, and may more accurately fit another type of distribution (e.g. triangular, lognormal, uniform, and truncated). Discretization of distributions may be complicated or inaccurate if distributions do not fit one of the standard types (normal, lognormal, etc.). Monte Carlo simulations may be computationally simpler and more accurate if a large number of parameters are assigned distributions.The reservoir-to-market methodology offers a robust approach to assess new projects that can take into account all of these and other qualifications and conditions.

SIGNIFICANCE OF RESULTS

Chemical flooding has gained little traction as a tertiary recovery strategy despite many mature onshore reservoirs existing that could be potential candidates. Decades of research have detailed technical challenges and successes through laboratory experimentation, chemical flood simulation, and some pilot projects, which have provided technical screening procedures to efficiently filter unfeasible projects. Therefore, technical understanding seems sufficient to advance projects through early development stages; however, a project value identification and realization process ultimately dictates project implementation in the oil and gas industry, with technical

feasibility merely supporting overall valuation and project feasibility. A quick early screening method integrating important project valuation criteria can efficiently assess many projects. The relatively few studies detailing chemical flooding valuation from just an economic standpoint reflects the need for an integrated process-oriented framework for quick early screening valuation of chemical flooding opportunities.

This study was significant in providing a robust, integrated process-oriented framework for early chemical EOR project screening, valuation, and decision-making. Chemical EOR project valuation and screening in the early development stages can help funnel a large number of projects and filter those that show potential value. Because many studies detail only the technical aspects of chemical EOR, with a handful including project valuation from an economic standpoint, there is a need for a process-oriented decision making framework that integrates all key project aspects (technical, economic, scheduling, equipment/facilities, etc.). Furthermore, if the need is addressed for quick valuation and screening of opportunities early in the project development phase, this helps focus development efforts on projects that have some assurance of being profitable.

These results were also significant in highlighting the importance of a benchmark for screening purposes, where a benchmark is essentially a representative standard or reference to serve as a starting point for building a reservoir-to-market model to value a project. Despite the scarcity and/or absence of commercial-scale analogues to calibrate and provide inputs for the benchmarks, a reservoir-to-market model benchmark for a mature oilfield was developed. Much of the importance in this benchmark was to demonstrate the process of creating a benchmark that could subsequently be adjusted to screen many other fields of similar nature. Additionally, using this model in a decision tree to assess multiple development scenarios is of direct relevance to decision making in the oil and gas industry.

FUTURE WORK

Future work should assess the uncertainty of integrated chemical EOR project development from a geological and reservoir perspective as well as an economic perspective. During early project development, geological uncertainty often has one of the largest effects on stock tank oil initially in place (STOIIP), which ultimately determines the volume of oil that can be delivered throughout the project life. Geological factors can include oil-water contact, and faulting and compartmentalization among other factors. Even if the reservoir dimensions and fluid volumes are known, uncertainty in reservoir parameters, particularly permeability, determines whether the STOIIP can actually flow through the reservoir and be produced. Green field development generally has much more geological and reservoir uncertainty than brown field (i.e. mature field) development.

Additional work may conclude the creation of benchmark models for certain field areas or regions to help screen chemical EOR project valuations. Although no two chemical EOR projects are exactly alike, this study focused on a mature, US onshore development as a benchmark; however, the work could be extended to develop a benchmark model for, say, an offshore project. The reservoir-to-market model should be applied to several different chemical EOR projects that have specifically defined production forecasts, scheduling, economics, and facilities inputs unique to each development. The output from these studies would provide more practical insight into project valuation and economics that through the piecemeal example used in this study.

An additional area of improvement would be to better define costs and uncertainty for inputs that may have a less project-specific nature. For example, several costs (e.g. chemicals, facilities, well recompletion, etc.) for a particular region may not change from field to field, and the uncertainty may be determined largely by market valuation at

particular times. Costs that are less project-specific can be accurately defined by field analogues and cost history, and prior knowledge of these cost structures would be useful when adapting a reservoir-to-market model to a particular chemical EOR project of interest.

Chemical EOR technology, particularly in research and development, is advancing rapidly. The Daqing ASP flood used as an analogue study in this research represents one of the largest chemical EOR multi-patterned pilots available in the literature with significant detail. However, the pilot was developed and implemented in the 1990s, and chemical EOR research has advanced significantly since them. Future work would modify the analogue data used to calibrate and validate the benchmark model to represent the latest technological advances in chemical EOR.

GLOSSARY

ASP – Alkali-Surfactant-Polymer, refers to a chemical EOR method employing the use of all three chemicals (alkali, surfactant, and polymer).

CDF – Cumulative Distribution Function, is the probability that a parameter will have a value less than or equal to a given value.

EDF – Excess Distribution Function, is the complement of the CDF.

EOR – Enhance Oil Recovery, which is a tertiary recovery process employing the use of items such as chemicals, steam, or miscible gas.

FID – Final Investment Decision, the point during a project development timeline that the decision to go ahead with the project execution is made.

GBM – Geometric Brownian Motion, a type of oil price model using a 'random walk' where prices randomly vary based on pre-defined volatility and current price.

IRR – Internal Rate of Return, which is a certain discount rate that makes the NPV of all future cash flows equal to zero.

MR – Mean Reversion, a type of oil price model similar to Geometric Brownian Motion, but includes an average price at which the 'random walk' can revert back to.

NPV – Net Present Value, which is the sum of the present values (PVs) of net cash flows expected at future points in time.

Payback period – The period of time required for returns to fully repay the original investment cost.

PDF – Probability density function, is the relative likelihood of an parameter to have a given value

PV – Pore Volume, the total volume of pore space in, say, a laboratory core, or a field volume (e.g. five-spot).

SFB – Synthetic Formation Brine, a brine solution commonly made in a laboratory setting that represents the ionic makeup of actual formation brine from a particular field.

SP – Surfactant-Polymer, refers to a chemical EOR method employing the use of surfactant and polymer chemicals, without the use of alkali.

UTC – Unit Technical Cost, which is the cost per produced volume of hydrocarbon.

VIR – Value Investment Ratio, which is the ratio of the present value of all future cash flows (NPV) to the present value of initial capital expenditures.

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